Open Innovation's Imact on Performance: A Case of an Indian IT Cluster

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Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

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Abstract

Open innovation (OI) is the capability to innovate through the use of purposive inbound and outbound knowledge flows to benefit firms driven by external knowledge and internal innovations. Inter-firm knowledge exchange and innovation occur in organisations operating within the same supply chain. Geographic separation between organisations however may limit collaborative opportunities for businesses to reduce costs, improve efficiency and support innovation. Organisations co-locating within the close proximity are more likely to facilitate inter-firm interactions, collaborate on resource utilisation and sharing of ideas and knowledge. In recent years, there has been a growing interest among academics, government agencies and private organisations to examine the scale, characteristics and capability of IT clusters such as the 'Silicon Valley' and Hyderabad 'Hi-tec city' clusters to support OI to help stimulate economic growth, improve productivity and promote inclusive development.

While there is evidence to show the benefits of geographic clustering for firms, the effect of agglomeration economies in stimulating OI however has neither been theorised nor empirically validated. Moreover, the collaborative processes through which OI and technological spill-overs are fostered within and outside an IT cluster are not well understood. Earlier studies have developed theoretical frameworks to conceptualise Open Innovation and Innovation Performance in the context of a developed world; nonetheless there is relatively little known about OI in firms in developing and emerging economies. This warrants an examination of the role of clusters in shaping OI activities within and outside an IT cluster with a particular focus on emerging economies.

Drawing on the Cluster Theory, Resource-Based View, Relational View and Absorptive Capacity, a theoretical model is developed to investigate the effect of geographic proximity on OI and innovation performance of IT organisations. This thesis developed a model and examined the relationship between OI and innovation performance as higher-order constructs and their underlying constructs driving innovation inputs.

This thesis adopts a quantitative approach to model the relationships between OI and degree of openness, stakeholder engagement, innovation practices and knowledge spill-overs. An online survey questionnaire was administered to 346 organisations in and outside the Hyderabad IT cluster in India. Constructs were operationalised and pre-tested through expert evaluation. Pilot testing was carried out to assess reliability and construct validity. The measurement and structural models were tested using the structural equation modelling technique.

The results show significant differences in OI and innovation performance among IT organisations within and outside the IT cluster. Organisations, which are geographically bounded tend to participate more in OI activities when compared to those which are geographically separated. Organisations which are clustered show better innovation performance. A multi-group analysis reveals significant differences between the two groups in relation to inbound innovation, absorptive capacity and innovation performance. This is because of the geographic proximity of IT organisations. The results highlight the positive effect of OI activities on innovation performance. IT organisations with a higher absorptive capacity for absorbing inbound knowledge demonstrated better innovation performance. This demonstrated the importance of knowledge absorption capability in achieving higher innovation performance through open innovation.

The main contribution of this study lies in exploring the interconnectedness among IT organisations and collaborative processes on OI and innovation performance. From a management perspective, this knowledge will enable managers and policy makers to emphasise OI to achieve better innovation performance. This knowledge will provide both government decision makers and IT managers with definite OI implications for innovation performance. Local governments can benefit from the results of this study in terms of implications for investment in IT clusters as well as incentives for IT organisations to set up their businesses within a designated zone. The major limitation is that this thesis utilised the data collected from organisations within and outside the Hyderabad IT cluster. A future study into comparison of data collected from various IT clusters could offer an in-depth understanding on the impact of clustering on OI and innovation performance.

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List of Abbreviations

AC	Absorptive capacity
AVE	Average variance extracted
BCHEAN	Business College Human Ethics Advisory Network
BPO	Business process outsourcing
BTOS	Bartlett's test of sphericity
CFA	Confirmatory factor analysis
CFI	Comparative fit Index
CR	Construct reliability
CT	Cluster Theory
EFA	Exploratory factor analysis
GOF	Goodness of fit
IFI	Incremental fit indices
IP	Intellectual property
IT	Information technology
KMO	Kaiser-Meyer-Olkin
MAR	Missing at random
MCAR	Missing completely at random
MI	Modification indices
MNF	Multinational firm
NFI	Normed fit index
OAR	Observed at random
OI	Open innovation
PCA	Principal component analysis
PCFI	Parsimony comparative fit index
PICF	Participant Information and Consent Form
PNFI	Parsimony normed fit index
R&D	Research and development
RBV	Resource-based view
RMR	Root mean square residual
RMSEA	Root mean square error of approximation
RV	Relational view

SEM	Structural equation modelling
SFL	Standardised factor loading
SMC	Squared multiple correlation
SME	Small and medium sized enterprises
SR	Standardised residual
SRMR	Standardised root mean residual
TLI	Tucker-Lewis index

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List of Published Papers

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Chapter 1: Introduction

Innovation capabilities are critical for organisations to sustain business continuity and enhance performance to remain competitive in a globalised marketplace. Geographic clustering of firms creates a convivial business environment for open innovation (OI). However, the role of clustering in building OI capabilities of organisations and its impact on overall innovation performance of IT organisations is yet to be thoroughly examined. This PhD study draws from the cluster theory (CT), resource-based view (RBV), relational view (RV) and absorptive capacity (AC) perspectives to examine how clustering can pave the way for OI and innovation performance. In particular, it investigates the relevance of the co-location of IT organisations to OI and innovation performance.

This chapter provides the background to this research and a detailed description of the problems identified. To understand the role of the co-location of organisations in promoting OI, Section 1.1 provides an overview of the research context within which the scope of this study is defined. Section 1.2 identifies the research problems and establishes the need to develop a new theoretical model to link OI and Innovation performance within a clustered environment. Section 1.3 presents the research gaps. This is then followed by the research rationale in Section 1.4 that outlines the scope and significance open innovation and growing need to create a favourable business environment. Section 1.5 establishes the research aim and sets out the research questions. Section 1.6 provides a synopsis of chapters in this thesis. Section 1.7 defines the key terms. Finally, Section 1.8 provides a summary of the contents presented in this chapter.

1.1 Research Background

Globalisation has rapidly changed the business dynamics around the world, introduced uncertainty in the global business markets and escalated fierce inter-firm competition. Organisations around the world aggressively pursue strategies to stay ahead of their competitors, but many struggle to cope with changing market conditions and volatile customer demand for new products and services (Valacich & Schneider 2014). To adapt to the constantly evolving business environment and develop agility, organisations are increasingly required to develop an innovative culture, which focusses on continuous development, integration and reconfiguration of creative skills and innovative capabilities to develop customer-driven products and services.

Coupled with an innovation culture, the co-location of firms can promote inter-firm participation and collaboration in research and development projects (Chesbrough 2006). The literature in the area of agglomeration economies also suggests that spatial clustering enables organisations to utilise knowledge acquired through spill-overs effect to achieve competitive advantage and improve their standing in the competitive world (Carlson & Wilmot 2006; Ellison & Glaeser 1999). The new policy shift in developing countries emphasises a planned transitioning from a decentralised industrial zoning model to a specialised enterprise cluster model, to facilitate business networking, collaboration opportunities and knowledge flows across business networks (Chesbrough 2006).

There has been many decades of research carried out on industrial districts, regional clusters and localisation of industries. Over the years, countless theories have been developed to illustrate the reasons why organisations in a specific value chain tend to operate from the same location (Swords 2013). The term 'agglomeration' was first coined by Marshall (1916; 1920) to illustrate the externalities observed in specialised industrial districts. An early mathematical model of the location theory proposed by Weber (1929) used a 'location triangle' to suggest that cost savings can be achieved through the selection of an optimum location for producing goods. Other location theories highlight location importance similar to that of cluster theory (Rigby & Zook 2002). The methodical approach by Porter (2003; 2008) amalgamated different approaches to develop a comprehensive cluster model to highlight collaborative as well as competitive benefits for firms from co-location within a geographically bounded space.

Porter (2000, p. 16) defines clusters as a 'geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities'. Mohring (2005, p. 29) believes that agglomeration economies enable business networks, and defines clusters as 'an agglomeration of vertically and/or horizontally linked firms operating in the same line of business in conjunction with associated institutions'. A cluster is a group of independent companies and associated institutions that are geographically concentrated in one or several regions, even though the cluster may have global extensions; specialised in a particular field, linked by common technologies and skills; and either science based or traditional'. Chesbrough (2006) states that clusters are a group of related firms in a geographical proximity with opportunities for innovation through technological spill-overs. In particular, IT clusters can be seen as a group of inter-related companies that cooperate and compete within a geographic location. IT clusters offer opportunities for OI through technological externalities including technological information and knowledge spill-overs, increased absorption and speed of technological upgrading, technological complementarities, reduction of technological investments, sunk cost and access to tacit knowledge (Antonelli 1994; Belussi 1999; Belussi & Arcangeli 1998).

In recent decades, local economies around the world have been integrated into the global economy. It has been argued by the proponents of agglomeration theory that clusters strengthen local economies and help them become focal points of regional growth (Akram et al. 2011). In fact, several nations, viewing clusters as catalysts for economic growth, have adopted the idea of agglomeration economies as a core component in their economic building and development strategies (Ali 2012; Wickham 2005), and policy makers have utilised cluster theories to stimulate regional economic growth. Although much has been integrated in regional policy and industrial planning, the cluster theory proposed by Michael Porter has been recognised in the field of business worldwide.

According to Porter's (2000) cluster theory, organisations can achieve dynamic capabilities through agglomeration economies that facilitate technological spill-overs and enable development of new business networks and knowledge sharing among organisations in a cluster. Clusters not only facilitate technological spill-overs, but lay a foundation for the idea of collaborative processes that support OI (Chesbrough 2006). Porter (2000) explains that the characteristics of the industry have little impact on performance unless organisations participate in innovation activities and improve their capabilities.

The accumulation of hi-technology organisations in a designated industrial zone creates ambience to attract highly skilled workers (Krugman 1991) that in turn allows organisations to achieve specialisation and adjoining capabilities (Stigler 1951). IT clusters in Silicon Valley, US, and Hyderabad Hitec City in India support local economies, offer new employment opportunities to local communities and facilitate knowledge spill-overs (Carlson & Wilmot 2006). Because of the unique opportunities associated with clusters, several nations have taken steps to create land banks and infrastructure to enable organisations to set up businesses within close proximity (Carlson & Wilmot 2006; Schilling & Logan 2013).

Knowledge spill-overs are externalities resulted in by commercial activities with external agents who are unable to fully take advantage of their own research and development (R&D) activities (Dumont & Meeusen 2000). Although knowledge is a valuable asset, but at times it is difficult for organisations to confine this accrued knowledge within their organisational boundaries. The organisations within the geographic vicinity or supply chain may absorb knowledge created by other firms without paying for productivity gain. Spill-overs may also be caused when inventors do not have control over the knowledge they created (Grossman & Helpman 1991). Organisations with a central role in the value chain will have a greater number of connections with other member organisations. As a result, peripheral organisations might gain the benefits from the central organisation's accomplishments by adapting their own practices (Argyres & Mayer 2007). Knowledge spill-overs are generally caused by the voluntary exchange of information, movement of workforce from one organisation to another and interactions between employees and stakeholders; however, the benefits of knowledge spill-overs fade with distance (Almeida & Kogut 1999). This forms the basis for clustering of organisations which are benefited from knowledge spill-overs.

Clusters not only offer interaction opportunities for collaboration but also drive innovation. Innovation is the process of creating and delivering new value to meet the needs of customers, suppliers or the organisation (Carlson & Wilmot 2006). Innovations triggered by unique ideas are proven to support business growth and overall performance (Ford 1996; Goetz 2011). To achieve the benefits associated with innovation, some organisations have adopted innovation strategies such as collaborative innovation (Carlson & Wilmot 2006; Goetz 2011). Literature also highlights the role of innovation strategies on the development of new products and services (Chesbrough 2006; Goetz 2011).

Innovation is considered essential in high-technology industries, such as IT, for organisational growth and success (Valacich & Schneider 2014). However, innovation comes at a cost and not all organisations possess the necessary resources for ongoing R&D activities (Chesbrough 2006). As clusters stimulate inter-firm cooperation and collaboration, firms can promote purposive knowledge flows to overcome challenges associated with resource and budgetary constraints of R&D activities through OI projects.

Open innovation (OI) is the innovation capability achieved through the use of purposive inflows and outflows of knowledge (Chesbrough 2006, 2003; Morris, Kuratko & Covin 2008). It is the most topical concept in the area of innovation management (Huizingh 2011). The core concept of OI is to expand innovation processes to industry stakeholders including rival organisations, educational institutions and other interested parties for the purpose of knowledge exploration and exploitation (Chesbrough 2006). The initial definition of open innovation proposed by Chesbrough (2003) does not provide a clear distinction between the inbound and outbound purposive knowledge flows. Van de Vrande et al. (2009) attempted to separate purposive knowledge flows into inbound and outbound innovation by elaborating on the activities associated with each of them. However, there is still an ambiguity in defining the open innovation concept as earlier studies failed to show a clear distinction between inbound and outbound purposive knowledge flows. In addition, the open innovation constructs are not operationalised in a comprehensible manner. Earlier studies (Barge-Gil 2010; Greco, Grimaldi & Gricelli 2015; Rangus & Drnovsek 2013; Stanislawski 2015; Vand de Vrande et al. 2009) explored one or few dimensions of open innovation at a time. Hence, a working definition of OI is developed on the basis of literature review on previous works to develop a comprehensive model for measuring open innovation.

The OI model helps organisations to acquire new knowledge and build on existing knowledge to create and commercialise innovations. However, the involvement of external partners in the form of collaborations and alliances has proven to be difficult yet critical for business success (Granstrand & Holgersson 2014).

OI offers several benefits including cost and time savings in innovation projects, knowledge flows among partnering organisations and generation of profits through the sale of intellectual property (Chesbrough 2006; Huizingh 2011; Morris, Kuratko & Covin 2008). Although the concept of OI is not very new, yet its contribution towards knowledge creation, sharing and exploiting through strategic partnerships with external firms in the same cluster is weakly theorised.

OI requires the increasing propensity of firms to work across their traditional organisational boundaries of operations (Mina, Moreau & Hughes 2014). OI requires collaboration and participation from external parties (Chesbrough 2006). In addition to relationships and social networks, cluster configuration plays a key role in promoting new collaborative and innovation practices among members. These value-creating practices have a positive impact on new product development projects in a cluster (Tracey, Heide & Bell 2014). For example, value creating practices such as collaborative partnerships drive innovation performance (Chesbrough 2006). The OI model encourages organisations to share their knowledge and resources with other firms that are not central to their strategy (Morris, Kuratko & Covin 2008). Technology giants such as Intel, IBM and Phillips pursue innovations through OI models because of the benefits such as access to external knowledge sources and a shorter time to develop and market unique products and services (Allio 2005; Chesbrough 2006).

Knowledge originating from external organisations contributes to the development of new products and services and help organisations to stay ahead of the competition (Chesbrough 2006). Phene, Fladmore-Lindquizt and Marsh (2006) studied the importance of innovation culture and found that the adoption of collaborative innovation strategies fuelled innovation. They also presented a study to create breakthrough innovations and how their study can be replicated in countries with a similar culture. However, there seems to be limited research in developing countries. Until recently, organisations developed business models that were focussed on encouraging innovation internally to a large extent and ignored the benefits of knowledge created by external firms. Afua (2009) argued that inventions are easy to imitate and even if organisations are continuously innovating, it is difficult to maintain eminence because of the inventions of others in the same field (Trompenaars & Turner 2010). In addition, resource constraints can reduce an organisation’s innovation performance, and failure to utilise innovations can lead to the exploitation of these innovations by other firms (Chesbrough 2003). Multinational firms (MNFs) have access to up-to-date technologies and critical resources (Rugraff & Hansen 2011), but it is likely that competitors will acquire similar or better technological solutions, triggering fierce competition and rendering the current technology unsustainable (Carr 2003).

Development of new products and services can offer new opportunities, which are difficult to imitate (Afua 2009). Promoting innovation culture can trigger interest among staff in the organisation, but sustainable investments in R&D can help utilise internal resources to develop new products and services (Chua, Roth & Lemoine 2015; Thong & Lotta 2015; Kim & Yoon 2015). Access to outside knowledge, expertise and resources can shorten the development life cycle and help to create innovative products and services at a lower cost (Chua, Roth & Lemoine 2015; Davis, Richard & Keeton 2015). This has been one of the main drivers for collaboration among firms and industry-wide supply chain networks (Jayaram & Pathak 2013).

While increased awareness of knowledge utilisation in innovation and creation of competitive advantage are the key driving forces behind collaboration among firms, information technologies facilitate a free flow of information indefinitely, to exchange ideas in a global but networked environment (Chua, Roth & Lemoine 2015; Fahy, Farrelly & Quester 2004; Jayaram & Pathak 2013). A combination of human capital, key resources and support for the local government in the form of policies and support mechanisms can have a positive influence on a collaborative environment. Afua (2009) suggests that joint ventures and strategic alliances can offer long-term benefits to all participants. Moreover, these strategic partnerships in R&D can enable new opportunities by providing access to a wide range of resources. Trompenaars and Turner (2010) explain that organisations can benefit significantly if internal developments and knowledge are combined with external in OI.

Indian IT organisations are mainly service providers to other organisations. Their business model is built around an outsourcing concept where organisations contract out some or all IT functions, such as management of IT systems, networks and other technical areas, to service providers (Saith & Vijayabaskar 2005). They have enjoyed the status of the most preferred destination for outsourcing for the last two decades, however, face many challenges because of competition from overseas IT organisations, customer demand for innovative products and services, longer development cycles and excessive costs associated with innovation projects. In the view of competition and maintaining their status as a preferred offshore destination for outsourcing, innovation is critical for Indian IT organisations to respond to global technological discontinuities (Mukundan & Thomas 2013).

Innovation capabilities can help organisations to compete, but resource constraints slow the progress of R&D efforts. While clusters support collaborative partnerships and interactions among organisations within, there needs to be a mechanism for purposive knowledge flows. Chesbrough (2003; 2006) explains that organisations in a cluster with an OI model tend to overcome resource constraints and show higher innovation performance (Huang & Rice 2012).

This section presented the importance of innovation for businesses in a dynamic environment, the positive impact of networking and collaboration and the significance of geographic clustering of firms in improving networking and collaboration opportunities for open innovation and innovation performance. Based on literature review, this study argues that organisations within a geographic proximity will have better opportunities for networking and collaboration with nearby organisations to facilitate both inward and outward knowledge flows for improving innovation performance.

1.2 Research Problem

Indian IT firms have a growing reputation for providing high-quality value-added services at a lower cost, but they are faced with competition from the organisations in other countries. The development and success of the IT industry in India is considered important for the growth of the national economy (Saith & Vijayabaskar 2005). The Indian IT industry contributed 8% of national GDP growth and overall revenues reached almost US$150 billion in 2014–2015 (Statista 2015). IT services and business process outsourcing (BPO) are the two most important components of the Indian IT industry, with contribution to GDP growing from 1.2% in 1998 to 7.5% in 2012. According to Statista (2015), the IT industry contributed 5.8%, 6.1%, 6.4% and 7.5% to national GDP in 2008–2009, 2009–2010, 2010–2011 and 2011–2012 respectively. A

NASSCOM report suggests that ICT industry revenues increased by US$17 billion in 2015, to total US$146 billion (NASSCOM 2014) and global ICT industry revenues are expected to reach 1,357 billion euros by the end of 2016 (Statista 2015). Drivers for this growth are the significant developments in e-commerce and unprecedented levels of global interest (NASSCOM 2014).

There are number of challenges faced by the Indian IT industry. Firstly, organisations in the Indian IT industry are mainly service providers for overseas multinational companies. Their core business pertains to providing services based on client requirements (Mehta 2016). The majority of these organisations are behind in terms of innovation. However, there are challenges with outsourcing (Varajao, Cruz-Cunha & Fraga 2017). In addition, of the top eight global outsourcing cities listed by Global Services Media, six are from India. The service provider business model is capable of earning significant profits, but competition from organisations in other countries has intensified, particularly in the Philippines, China, Ireland, Brazil and Canada.

Secondly, Indian IT organisations were mainly focussed on providing offshoring services to their overseas customers by benefitting from the lower labour costs of highly skilled IT professionals in India (Wang, Huang & Wu 2012). Although India is among the top five offshore nations list for IT services, it is facing fierce competition from other countries (Tholons 2014). Cutthroat competition in BPO offerings, technological advancements and disruptive technologies such as cloud computing are putting further pressure on the Indian IT industry to remain competitive, as are educated clients demanding better value for money (Mehta 2016). As innovation capabilities are proven to improve business performance (Calantone, Cavusgil & Zhao 2002; Terziovski 2007), Indian IT organisations need to identify ways to improve innovation capabilities and operational efficiencies to stay ahead of the competition and maintain their position as the preferred IT and BPO solution providers (Mehta 2016).

Hadjimanolis (1999) explains that competition is seen mostly between organisations with nearly identical products and services with comparable prices; however, organisations can maintain competitive advantage with distinct products and service (Dey, Lahiri & Zhang 2014). Therefore, it is important for Indian IT organisations to develop high-quality products and services and improve business performance.

Thirdly, Capaldo et al. (2003) point out that firms lagging behind in introducing new products and services are usually considered poor performers in the industry. Srivastava and Shainesh (2015) assert that innovations can positively affect economic welfare, and present a case for promoting innovative business solutions. Mannan, Khurana and Haleem (2015) explain that lack of convincing collaboration projects with education institutions and R&D organisations, lack of in-house skills, high costs associated with innovation and failure to keep up with new technologies are some of the main barriers of innovation in India.

Finally, although Indian IT firms are improving their innovation capabilities, there are only three Indian firms that appear in the top 100 ranking of the world's most innovative companies. Of these three firms, only one represents the IT sector (Forbes 2015). This again suggests a need to boost innovation capabilities to maintain India's position as the most preferred offshore destination for IT. In addition, India's success is inherently associated with its competence in keeping pace with technology. To become a knowledge hub by 2022, innovation will have to play a significant role (FRPT 2014), but this involves significant investments in R&D. Despite being the IT services capital of the world, Indian IT organisations lack a proactive approach to benefiting from the existing clusters and OI.

1.3 Research Gaps

From a theoretical perspective, the existing body of open innovation literature has assisted in understanding the benefits associated with open innovation activities in organisations of developed economies, however there are very few studies on the relevance of open innovation in developing economies such as India. In fact, these were limited to studying the role of open innovation in manufacturing organisations. Moreover, it is unclear about what activities are critical for open innovation and innovation performance and remain unaddressed.

The open innovation constructs are not operationalised in a comprehensible manner. Earlier studies (Barge-Gil 2010; Greco, Grimaldi & Gricelli 2015; Rangus & Drnovsek 2013; Stanislawski 2015; Van de Vrande et al. 2009) explored one or few dimensions of open innovation at a time. These approaches provide a limited understanding on the dimensions of open innovation and the importance of some dimensions over the other in improving open innovation and its relevance to innovation performance. This warrants the need for research on integrating the open innovation constructs in a structural model to understand the role of various constructs in facilitating open innovation and innovation performance.

From a market perspective, the opening of domestic market to foreign entities may lead to industrial transformation and economic revolution (Schumpeter 1942). In addition, participation of overseas organisations promote collaboration in research and development and also enhances knowledge transfer among participant organisations. Hung (2009) also explains that the Indian government's decision to allow foreign investments in 1991 facilitated access to higher technology and promoted exports. Literature also presents the benefits associated with the opening of domestic market to foreign entities. However, the innovation resulting from the relationship between domestic and foreign IT was not measured (Altenburg, Schmitz & Stamm 2008; Wang, Huang & Wu 2012).

From an IT industry perspective, innovation is vital for Indian IT organisations. However, there seems to be little evidence on Innovation studies in Indian innovation literature. Hung (2009) also points out that India's expenditure on science and technology projects is well below 1% of the national GDP. However, there has been an increase in the investments on science and technology projects in recent years, but the ratio of research and development personnel to the total labour force still remains low. Moreover, India lags behind US, Japan, Korea and Taiwan in terms of IT industry investments in research and development projects (Global competitiveness report 2003). This study on measuring open innovation in organisations located within and outside the IT cluster can reveal important information on ways to enhance innovation related activities through purposive knowledge flows.

From the practitioners' perspective, the current literature highlights the growing interest on studying the benefits of clusters. Although there is growing interest among researchers and government organisations in open innovation in clusters (Chesbrough 2006; Dahlander & Gann 2010), the literature presents limited information on improving innovation performance through OI in a clustered environment (Giusti, Alberti & Belfanti 2017; Huang & Rice 2013; Salvador, Montagna & Marcolin 2013).

Moreover, gaps also exist in linking clusters to open innovation and innovation performance. This suggests the need for a comprehensive study into the role of geographic proximity in facilitating collaboration opportunities for promoting knowledge flows among participants to improve innovation performance.

1.4 Rationale for the Current Research

There are several strategic management theories to help organisations improve their innovation capabilities. The most notable and relevant strategic theory, RBV, suggests that an organisation's competitiveness comes from utilising internal resources through the evaluation of opportunities and weaknesses (Raduan et al. 2009). RV outlines the importance of organisation networks in innovation capabilities (Dyer & Singh 1998). Whereas, absorptive capacity refers to the capability of a firm to recognise and apply external knowledge for innovation. It involves searching for, identifying and exploiting external knowledge and seizing opportunities as they arise to improve innovation capabilities (Cohen & Levinthal 1990). Based on earlier studies, the proposed research attempts to use CT, RBV, RV and AC theories to study the role of organisations' openness, stakeholder engagement, innovation practices and knowledge spill-overs in OI (inbound and outbound) and innovation performance in IT clusters.

First, OI is considered a general approach that allows firms to move away from a traditional closed innovation system to a new collaborative open approach to improve innovation capabilities. It allows firms to make use of external resources to develop new technologies, products and processes (Morris, Kuratko & Covin 2008). It also enables an inflow of external innovative ideas into the firm and allows internal ideas to exit and be utilised by external entities (Allio 2005). The flow of knowledge is greatly improved by the firm's geographic location, because of the spill-overs caused by worker movements in the industry, which are carried with them from one firm to the next (Krugman 1991). Scholars (Clancy et al. 1999; Rosenfeld 1997) have identified similarities between clusters and competitiveness. Competition and cooperation are the main reasons for interactions among organisations. These interactions can be increased through the geographic co-location of firms (Doeringer & Terkla 1995; Padmore &

Gibson 1998). Hence, this thesis seeks to study the influence of clusters in promoting OI and the factors that could improve innovation capabilities of Indian IT organisations.

Second, according to Griliches (1991), knowledge spill-overs are ideas absorbed from other firms in the same industry. They improve productivity, fuel internal innovation and support economic growth, as new knowledge helps improve processes. Scholars (Carlson & Wilmot 2006; Marshall 1916; Porter 1998) argue that knowledge spill-overs act as fuel for innovation, and suggest that a firm's geographic location is vital to its innovation performance (Chesbrough 2006; Porter 1998). However, the current literature is limited to detailing the benefits of external knowledge (Bernstein & Nadiri, 1987; Griliches 1995, 1991) and collaboration opportunities. This prompts a need to identify ways to facilitate knowledge flows. A study into understanding ways to promote and tap external knowledge would improve innovation performance (Leiponen & Helfat 2010; Love, Roper & Vahter 2013).

Third, OI is a multidimensional construct (Huizingh 2011). Previous research mainly elaborates the limitations of closed innovation and the benefits of OI (Cattaneo et al. 2011; Ketels & Memedovic 2008). Although sharing crucial information with stakeholders can be risky, it will be compensated by resulting innovations, paving the way for more open and collaborative innovation projects (Sheridan 2011). Both the practical and academic discussions have paid significant attention to the general view of OI, but little to the relevant constructs and their effect on OI (Nakagaki, Aber & Fetterhoff 2012) and the transition processes involved in moving from closed innovation to OI (Granstrand & Holgersson 2014).

Fourth, the literature (Ayuso et al. 2011; Chesbrough 2006; Jimenez-Jimenez & Sanz-Valle 2011; van de Vrande et al. 2009) provides limited information on OI constructs, degree of openness, stakeholder engagement, innovation practices, knowledge spill-overs, inbound innovation and outbound innovation and innovation performance. The vital question is how the system of innovation develops and evolves in an IT cluster to support OI. As firms continue to evolve and their surroundings appear to influence innovation activities, a more refined micro-level approach, with a particular attention to the usage of open models, is necessary.

Fifth, the geographic co-location of firms allows cooperation between firms and institutions, which are necessary for knowledge flows. However, government policies play an important role in cluster formation and achieving a conducive environment (Afuah 2009; Ray 2012). Hyderabad is the second biggest IT cluster in India and was initiated by the local government (Ramachandran & Ray 2006). The local government believes that the Hyderabad IT cluster has reached its capacity and there is a need to develop a new IT cluster (Shanker 2014). Studying the Hyderabad IT cluster can reveal important information on the importance of clusters and their role in OI and innovation performance, which can be used by the other governments to understand and establish new IT clusters.

Finally, Indian IT firms provide services to organisations in more than 75 countries and employ 12.5 million people both directly and indirectly (IBEF 2015). Indian IT services were worth about US$56 billion at the end of 2013 (IBEF 2015), reaching US$100 billion in 2015. This revenue growth is expected to reach US$200 billion in the next five years (Anand 2014), mainly due to the low cost of operations, the availability of educated and highly skilled labour; however, the Indian IT firms are gradually losing cost advantage (Chakraborty & Dutta 2002), because of cutthroat competition from the Philippines, China, Ireland, Brazil and Canada (Global Services Media 2009). Although India is among the top five preferred offshore destinations for IT services, there is limited investment in IT infrastructure and R&D by local IT organisations (OSeC 2011). To maintain this status as the preferred offshore destination for IT services and competitive advantage, it is necessary to continue innovation projects and utilise external knowledge resources for innovation performance. Given the above discussion, this thesis attempts to measure the level of OI and innovation performance in the Hyderabad IT cluster and compare it against organisations located outside the IT cluster.

1.5 Research Aim and Questions

This study aims to develop a comprehensive OI framework to measure open innovation and model its effect on innovation performance of organisations within and outside the IT cluster and the mediating role of absorptive capacity in between open innovation and innovation performance. This study (1) operationalised the open innovation constructs and validated the scale to measure open innovation in organisations, (2) presented a comprehensive model to measure innovation performance resulting from the open innovation activities, (3) tested the mediating role of absorptive capacity in between open innovation and innovation performance, and (4) examined the role of geographic proximity on open innovation and innovation performance of IT organisations. The scope of this study is limited to IT organisations within and outside the Hyderabad IT cluster in India. The main research questions are:

RQ1: *What is open innovation and how do we measure it?*

RQ2: *Do the degree of openness, stakeholder engagement, innovation practices and knowledge spill-overs affect open innovation?*

RQ3: *Do inbound and outbound innovation activities drive innovation performance in IT organisations?*

RQ4: *Does the absorptive capacity of IT organisations influence innovation performance?*

RQ5*: Does clustering of IT organisations affect innovation performance?*

1.6 Thesis Structure

This thesis is organised into eight chapters, including this introduction chapter. The structure of the thesis is presented in Figure 1.1. The first chapter provided the research background, research problems, gaps and rationale, and then set out research aims and questions.

The second chapter presents the underlying theories of OI and its link to innovation performance. It theorises various dimensions of OI and their influence on innovation performance. This chapter presents various definitions of open innovation and innovation performance and sheds light on the likely linkages gathered from previous studies across various perspectives.

The third chapter presents key constructs to represent OI including degree of openness, stakeholder engagement, innovation practices and knowledge spill-overs, inbound innovation, outbound innovation and innovation performance. A conceptual framework based on the extant literature review will be presented in this chapter. The constructs determining OI are established and the research hypotheses are presented in this chapter.

The fourth chapter outlines the methodology adopted to address the research questions and hypotheses. In order to develop a comprehensive design, a research instrument and data-driven inquiry into addressing research questions, sufficient knowledge adjoining the topic area needs to be acquired (Cavana, Delahaye & Sekaran 2001). The research philosophies, research method and approaches considered appropriate for data collection and analysis for examining the hypothesised relationships of the proposed model are detailed.

The fifth chapter presents the steps adopted for data preparation and analysis. Then, it details the tests conducted on the normality of a sample to understand whether the sample distribution is normal and the approaches employed to address any abnormalities.

The sixth chapter outlines the steps followed to evaluate the validity and reliability of the measurement instrument used for this study. Then, it describes the reasons behind the use of scientific methods to test the validity and reliability of the instrument and to ensure that the research adopts proven and well-established practices

The seventh chapter presents the results of the structural model and Kruskal-Wallis tests. Then, a detailed discussion of the key findings is presented to address the research questions presented in chapter one.

The final chapter eight revisits the research questions presented in chapter one and then discusses the theoretical and practical implications, research limitations and future research opportunities.

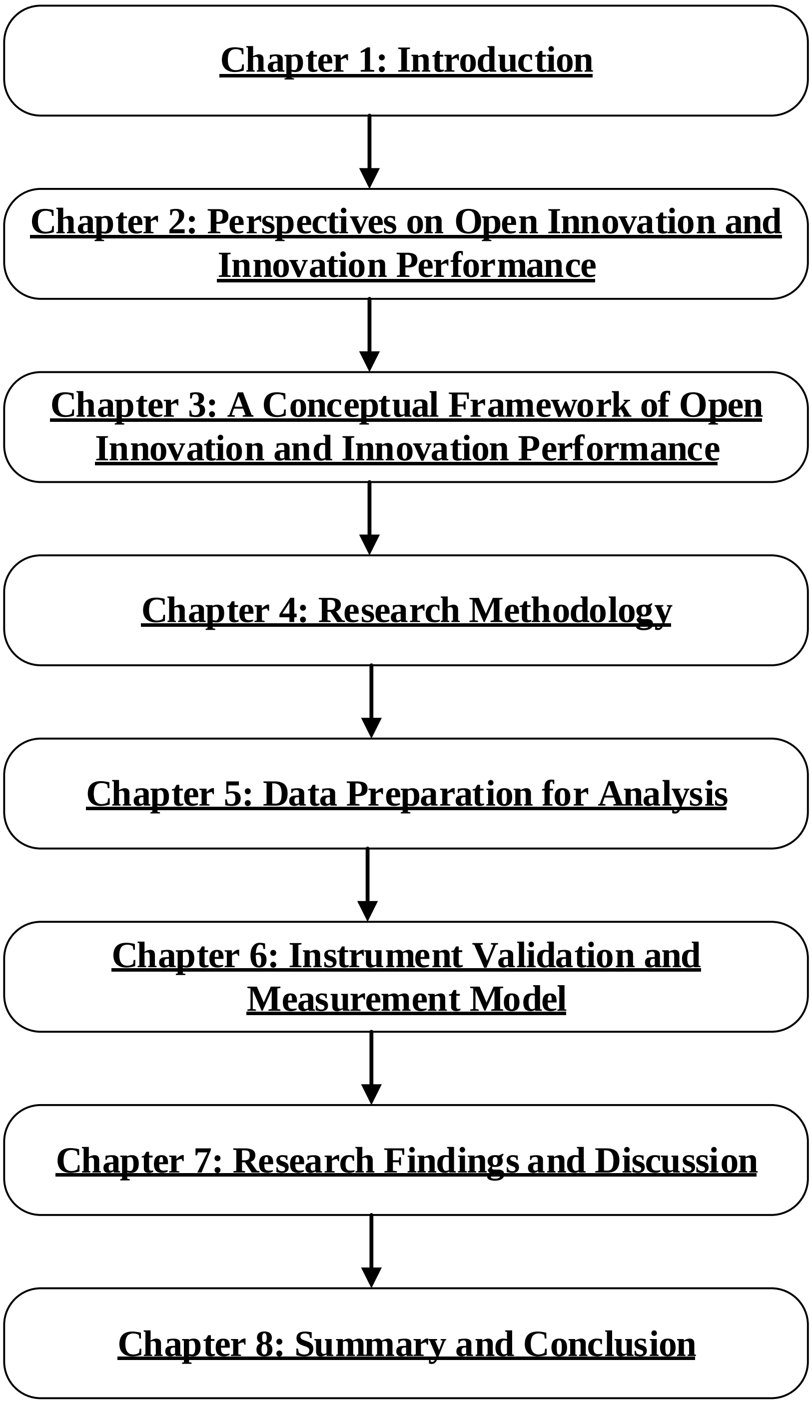

Figure 1.1: Thesis Structure

1.7 Key Terms

Degree of Openness

It is the organisation's propensity to cooperate with other firms in knowledge sharing activities.

Inbound Innovation:

Inbound Innovation refers to the exploration and exploitation of external resources and knowledge to support and fuel internal innovation efforts by opening up an organisation's innovation processes to the other firms.

Innovation Performance:

The benefits associated with the outcomes of organisational innovation processes.

Innovation Practices:

These are the efforts in the form of organisational processes associated with harnessing open innovation in the organisation.

Knowledge Spill-overs

It refers to the flow of knowledge which occurs through interactions between organisations and their stakeholders.

Outbound Innovation:

Outbound innovation refers to commercialisation of internal innovations and intellectual property rights to generate income for internal innovation by enabling processes to support outward knowledge flows.

Open Innovation:

A combination of inbound and outbound purposive knowledge flows to support and enhance organisation's research and development efforts.

Stakeholder Engagement

It is the level of participation by both direct and indirect stakeholders in open innovation activities.

1.8 Summary:

This chapter presented a research background to provide essential context on research problems, gaps and rationale for the research. The research problems, gaps and rationale are detailed. Based on the discussion, research aims and questions are presented. Then, a synopsis of the chapters in this thesis is presented. Finally, the key terms are defined.

Chapter 2: Perspectives on Open Innovation and Innovation Performance

2.1 Introduction

This chapter presents the concepts of OI and innovation performance and discusses various underlying theories of OI and innovation performance. Then, a conceptual framework will be developed in this chapter to theorise the relationships and interactions between OI and innovation performance using a range of perspectives.

Section 2.2 outlines the historical perspectives on OI and the OI model proposed by Chesbrough (2003). Section 2.3 defines the innovation performance concept and its dimensions and indicators to measure the scale, scope and magnitude. Section 2.4 identifies the causes of OI and their impact on innovation performance. Section 2.5 reviews the Resource based View (RBV) in the context of OI and innovation performance to highlight the importance of resources for firms to harness the opportunities. Sections 2.6 details the Relational View (RV) perspectives on OI and innovation performance to emphasise the value of relational capital. Section 2.7 highlights the importance of organisational capabilities in absorbing the knowledge gained through its networks and its relevance to OI and innovation performance. Section 2.8 discusses the Cluster Theory (CT) to reflect the role of space and the geographic proximity on OI and its impact on innovation performance. Section 2.9 presents an overview of RBV, RV, AC and CT theories and the measures of OI and innovation performance. Finally, Section 2.10 summarises the chapter.

2.2 The Concept of Open Innovation

Innovation is the ‘spontaneous and discontinuous change in the channels of flow, disturbance of equilibrium which, forever alters and displaces the equilibrium state previously existing’ (Schumpeter 1961). Innovation is the process of creating new customer value in the form of unique processes, innovative products and services (Chesbrough 2006). Innovations are critical for organisations as they allow new opportunities to emerge. They help improve processes, products and services, creates new business models to support new distribution channels, sustainable growth, gain competitive advantage and grow profits (Huang & Rice 2013). To improve innovation capabilities, firms need to make significant investments in research and development activities. However, there is no immediate return on investment in innovation. Moreover, the question of how organisations can minimise investment on internal R&D activities and improve their innovation capabilities with networks and sharing of resources has been debated yet remained unanswered for some time.

Chesbrough and Bogers (2014, p. 17) defined OI as 'a distributed innovation process based on purposively managed knowledge flows across organizational boundaries'. In the early 21st century, Chesbrough (2003) introduced the concept of OI to help fuel innovation mechanisms through knowledge flows. Since then, there have been several studies (Gassman & Enkel 2004; Huang & Rice 2013; Van de Vrande et al. 2009; West & Gallagher 2006) on OI as a strategic tool to support an organisation's goals to improve innovation performance. Many scholars (Chesbrough 2003; Teece 2010, 1986; van de Vrande, Lemmens & Vanhaverbeke 2006; von Hippel 1989, 1988) have contributed to the literature on OI and explored ways to improve innovation through inter-firm linkages and collaborative efforts.

Innovativeness and competitiveness of firms can be enhanced through absorbing new knowledge from external sources, which may lead to acceleration of organisations' innovation activities (Chesbrough 2003; Chesbrough, Kim & Agogino 2014; Martinez-Torres 2013; Van Geenhuizen & Soetanto 2011). New terms, such as 'collaborative innovation' and recently 'crowd sourcing', to explain OI. Chesbrough (2003) proposed the term 'open innovation'to capture innovation mechanisms that facilitate inter-firm interaction and mutually beneficial collaboration with external firms (Chesbrough 2003) through facilitating purposive bi-directional inflows and outflows of knowledge. Subsequently, Chesbrough (2006) argued that OI models facilitate knowledge exploration. Similar views were shared by West, Vanhaverbeke and Chesbrough (2006), which gathered evidence to support that purposive knowledge flows may create opportunities for market expansion. Purposive knowledge flows are deliberate attempts of firms to allow bi-directional knowledge flows (Chesbrough 2003).

The process of innovation involves identifying, developing and testing new ideas (Dosi et al. 1998). Traditionally, innovation activities are regulated and controlled within the organisational boundaries. However, there has been a dramatic shift in recent decade which places greater emphasis on customer preferences, advancements in technology and availability of a wide range of products and services. This in turn made the closed innovation unsustainable. Organisations are increasingly relying upon improved interactions with stakeholders in a broader ecosystem to access critical knowledge that enhances inter-research activities (Chesbrough 2003). This has led to wider adoption of the OI concept.

This popular model proposes that organisations should move away from the traditional closed innovation model to benefit from knowledge in the surrounding environment to support internal innovation efforts (Chesbrough 2003). Table 2.1 summarises various perspectives on OI.

Table 2.1: Perspectives on Open Innovation

Definition	Reference(s)
Use of purposive knowledge flows (inflows and outflows) to fast-track internal innovation	Chesbrough 2003
Open up the innovation processes to external stakeholders to promote smooth knowledge flows	Chesbrough 006
A combination of core processes, the outside-in process and the inside-out process aimed to bring in new knowledge and commercialise internal knowledge and innovations for profit	Gassmann & Enkel 2004
Systematically encouraging and exploring a wide range of internal and external sources for innovation opportunities, consciously integrating that exploration with firm capabilities and resources, and broadly exploiting those opportunities through multiple channels	West & Gallagher 2006
There are two types of OI, Inbound and Outbound. Inbound OI involves opening up an organisation's innovation process to source external knowledge. Whereas, outbound innovation processes enable organisations to share their knowledge with others	Litchtenthaler 2009; Van de Vrande et al. 2009

A fundamental basis of the OI concept (see Figure 2.1) is to (i) integrate both outside-in and inside-out processes to access external knowledge, (ii) create value for stakeholders and (iii) allow others to utilise resources through complementarities, alliances, cooperation and joint ventures (Chesbrough 2003; Su & Lee 2012; West, Vanhaverbeke & Chesbrough 2006). OI underscores that organisations may not possess all the necessary resources for R&D. To improve innovation capabilities, organisations need to employ mechanisms to absorb new technologies and knowledge (Markman 2016).

Further, OI enables organisations to harness knowledge flows for innovation success (Enkel, Gassman & Chesbrough 2009).

Figure 2.1 presents the open innovation model. According to Chesbrough (2006) new technology and knowledge enters into organisational processes through technology projects. The knowledge gained in the projects can go to market as out-licensing or technology spin-offs.

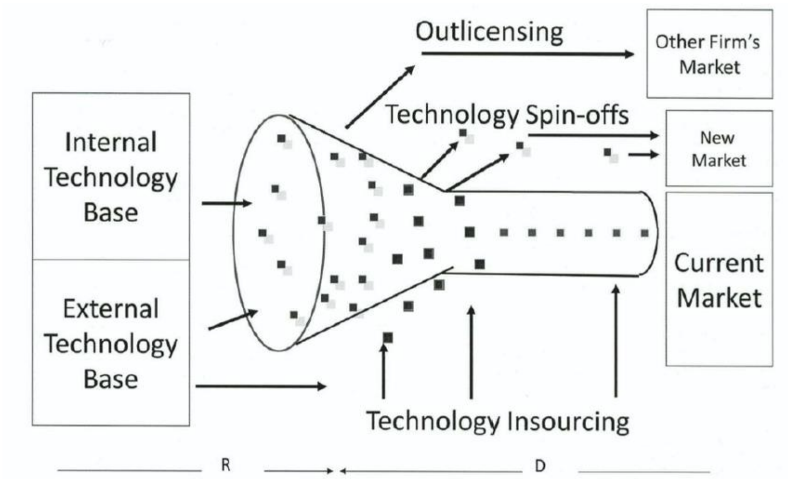

Figure 2.1: The Open Innovation Model (Chesbrough 2012, p. 23)

There are two types of OI: inbound and outbound (Van de Vrande et al. 2009). OI activities not only involve exploring external knowledge and combining it with internal knowledge, but also allow knowledge to be exploited by other organisations (Litchtenthaler 2011, 2008) and combining inbound and outbound OI processes (coupled process) (Gassmann & Enkel 2004).

Inbound OI (outside-in) involves opening up an organisation's innovation process to source external knowledge, while outbound innovation processes enable organisations to share their knowledge with others (inside-out) (Litchtenthaler 2009). Outbound innovation activities occur in the form of both non-monetary (improvements) benefits as well as monetary benefits (sale of intellectual property (IP) rights) (Ahn, Minshall & Mortara 2015; Dahlander & Gann 2010).

Based on the literature review, this study defines open innovation as a combination of inbound and outbound purposive knowledge flows to support and enhance organisation's research and development efforts. Table 2.2 presents open innovation case studies.

Table 2. 2 Open Innovation Case Studies

Organisation	Description	Motivators for OI	OI activities	OI results	Reference(s)
Butantan Institute	A science & technology institute in Brazil Manufacturer and supplier of immunobiological products including hyper immune sera and vaccines	Integrates scientific & technological research Concern to disseminate the knowledge derived from its research	Technology transfer Licensing technologies	Established relationships with other organisations Technology transfer agreements signed to access new technologies. Licensing agreements are established with pharmaceutical companies to allow the use of its intellectual property	Leme et al. 2015
Natura	A Brazilian manufacturer and leader of beauty products Its strategy is based on innovation	Communication improvement (internal and external)	Establish agreements with universities	Formal agreements with universities for collaborative innovation	Ades et al. 2013
IBM	IBM is an information technology company with the aim to implement an innovation laboratory in Brazil Leader in the number of patents in the US with more than 4,500 patents	Unable to use the patents Unable to manage the knowledge generated in their labs	Establish agreements with universities Funding support to research students	Formal agreements with universities for collaborative innovation	Ades et al. 2013

Siemens-Chemtech	An engineering and software division of Siemens group More than 100 employees with a headquarters in Brazil	Communication improvement between R&D and other functional units	Establish agreements with universities	Formal agreements with universities	Ades et al. 2013

The OI model is now relatively well recognised accross various sectors (Enkel, Gassmann & Chesbrough 2009; Teece 1986; van de Vrande, Lemmens & Vanhaverbeke 2006; von Hippel 1988). While there have been several studies on the benefits of OI (e.g., Christensen 2005; Laursen & Salter 2006; Lichtenthaler 2009), earlier studies were largely focussed on highlighting the benefits of OI across larger firms (van de Vrande et al. 2009), such as AT&T, IBM, Microsoft, Phillips and Proctor & Gamble (Chesbrough 2003). Whereas, recent studies have explored challenges in relation to both closed and open innovation (e.g., Christensen 2005; Laursen & Salter 2006; Lichtenthaler 2009).

Felin and Zenger (2014) used the innovation problem as the unit of analysis to study various governance models in relation to communication channels in exchanging knowledge, types of incentives and the value gained through innovation to develop a framework for managing innovation. They found out that the optimal governance of innovation is contingent on the nature of the innovation problem to be solved. Garriga, Krogh and Spaeth (2013) assessed the importance of adopting search strategies to identify external knowledge sources. Their findings revealed that use of external knowledge in internal R&D is linked to efforts made by firm to adopt and implement search strategies. Appio et al. (2017) point out that searching for knowledge over time may lead to identifying new knowledge. Undoubtedly, success stories such as the Silicon Valley created a wider interest among policy makers, but firms need to be prepared for challenges while transforming to OI models (Nakagaki, Aber & Fetterhoff 2012). This is because transformation is associated with extensive changes to organisational processes. Although encouraging staff to participate in innovation activities and allowing them to interact with external stakeholders can help develop innovations and discover ways to market these innovations, firms may need to undergo significant changes such as redefining tasks and boundaries to facilitate interactions with external parties (Salter, Criscuolo & Wal 2014). Bucic and Ngo (2012) surveyed representatives from medium and large Australian companies participating in collaborative ventures and found that formal coordination mechanisms, organisational structure and internal processes play a major role in collaborative innovation. This view is supported by Makimattila, Melkas and Uotila (2013), who observed the dynamics involved in innovation processes in the Finnish food industry and found that interactions were critical in innovation processes.

This section defined open innovation and detailed various perspectives of open innovation. This section also presented the importance of open innovation for firms and earlier studies in relation to open innovation.

2.3 The Concept of Innovation Performance

'Innovation performance' is the result of the efficiency and effectiveness of the innovation activities of an organisation (Neely, Gregory & Platts 1995). It is a multi-faceted concept as it looks at both efficiency and effectiveness of innovation mechanisms. Innovation efficiency is characterised by the process, product and service improvements achieved through the utilisation of organisational resources using unique ideas; while innovation effectiveness refers to achieving goals by aligning innovation processes with organisational goals. Table 2.3 presents indicators for innovation performance. Scholars have offered various definitions for innovation performance, and used efficiency and effectiveness to measure it. For example, Neely, Gregory and Platts (1995) and Hanifah et al. (2017) used both efficiency and effectiveness. Whereas, Zizlavsky (2016) considered effectiveness alone to measure innovation performance.

Literature highlights the need for innovation and its role in supporting organisation growth and performance (Chesbrough 2006; Huang & Rice 2012; Markman 2016; Romer 2006; West & Gallagher 2006). Although innovations are considered critical for sustainable growth (Zizlavsky 2016), the majority of organisations are left behind in measuring innovation performance (Skarzynski & Gibson 2008). Earlier studies explored ways to measure innovation efficiency and effectiveness through key performance indicators.

Table 2.3: Innovation Performance Dimensions and Indicators

Reference	Definition	Dimensions	Indicator
Neely, Gregory & Platts 1995	The result of the efficiency and effectiveness of the innovation activities of an organisation	Efficiency Effectiveness	Processes
Hanifah et al. 2017	The use of novel ideas to improve the effectiveness and efficiency of products, processes and services	Efficiency Effectiveness	Products Processes Services
Zizlavsky 2016	The benefits associated with the outcomes of organisational innovation processes	Effectiveness	Products Processes Services Intellectual property

Table 2.4 presents empirical studies on innovation performance dimensions and key performance indicators across various industries. Venkatraman and Ramanujam (1986) suggest the use of both economic and non-economic indicators, where economic indicators represent profit margins, cost savings and returns on investment, and non-economic indicators refer to quality aspects of product, process and service, customer satisfaction and agility. Earlier studies adopted either or both of these indicators to measure innovation performance (Carroll et al. 2017; Gao & Chou 2015; Santa, Hyland & Ferrer 2014; Sarkees & Hulland 2015).

Consistent with Venkatraman and Ramanujam (1986), various studies have adopted a both efficiency and effectiveness to measure innovation performance; however, the use of both efficiency and effectiveness is debated vigorously in the literature. For example, Carroll et al. (2017) and Gao and Chou (2015) argue that earlier approaches of combining both efficiency and effectiveness to measure innovation performance were inadequate as these studies used long-term economic indicators such as the number of patents, ignoring the importance of non-economic indicators. Santa, Hyland and Ferrer (2014) argue that the use of non-economic indicators to measure innovation performance would help assess the contribution of various business processes. In addition, the use of non-economic indicators can help measure both efficiency and effectiveness of innovations in terms of process, product, service and intellectual property improvements. Hence, this study uses non-economic indicators to measure innovation performance.

Table 2.4: Empirical Studies Measuring Innovation Performance through Key Performance Indicators

Reference	Dimension		Key Performance Indicators	Industry	Country
	Efficiency	Effectiveness			
Carroll et al. 2017		✓	Investments Returns Opportunities Network capabilities	Pharmaceutical	US
Santa, Hyland & Ferrer 2014		✓	Service quality User satisfaction	Service sector	Australia
Sarkees & Hulland 2015	✓		Products Processes Services Relationships	Cross-industry	US
Gao & Chou 2015	✓		Patents	Pharmaceutical	US

2.4 Sources and Causes of Open Innovation and Innovation Performance

Based on literature review, four key perspectives are identified: RBV, RV, AC and CT (cluster theory). Table 2.5 provides a summary of the four key perspectives on OI and innovation performance and the subsequent sections detail each of these four viewpoints.

Table 2.5: Key Perspectives on Open Innovation and Innovation Performance

Perspective	Key arguments	Strengths	Weaknesses	Implication	References
RBV	Organisation's valuable, rare and non-substitutable resources determine the growth of the firm	Explains the role of resources in laying a foundation for a collaborative environment that helps to reach a desired capability	The preliminary condition for a firm is to acquire rare and valuable resources	The RBV has identified various motives for collaboration, AC and bridging the gap between existing and desired capabilities in a short time frame	Barney 1991; Dyer & Singh 1998; Kogut 1988; Kogut & Zander 1992; Mowery, Oxley & Silverman 1996; Penrose 1959
RV	Access to external complementary resources can be necessary to achieve sustained growth RV offers an important perspective to study cooperative strategy in multi-firms, and is applicable for firms to improve their performance in OI	Highlights the need for sharing rare and unique resources with other firms to enhance innovation capabilities	Resource heterogeneity is the preliminary condition Lacks practical relevance to imperfect mobility of resources and ongoing relationship with partners	Firms engage in strategic alliances to aggregate, share or exchange valuable resources with other firms Emphasises on common benefits that collaborative partners cannot generate independently	Das & Teng 2000; Dyer & Singh 1998; Teece 2007, 1986; Zhu, Zhong & Mei 2013
AC	The firm's capability to identify, absorb and integrate new external knowledge into its innovation processes help transform internal operations, products and services	Helps firms to identify, assimilate and utilise knowledge to meet their innovation needs	In the outbound OI process, firms with strong 'desorptive capacity' voluntarily disclose knowledge to less-informed economic agents AC does not	In this regard, a firm's knowledge management capacity not only mediates openness and performance but also affects 'search' (inbound OI) and 'desorptive' capacity (outbound OI)	Ahn et al. 2016; Arbussa & Coenders 2007; Lichtenthaler & Lichtenthaler 2009; Mortara & Minshall 2014; Van Der Meer 2007

			consider the role of desorptive capacity, which is critical for outbound innovation		
CT	Clusters lay a foundation for the idea of collaborative processes that support OI	Explains how geographic concentration of firms can enable collaboration and knowledge sharing opportunities	Excessive concentration may lead to environmental conflict and technology obsolescence	Clustering enables organisations to explore and exploit knowledge in the surrounding environment	Chesbrough 2006, 2003; Mazur et al. 2016; Vanhaverbeke 2006; West & Gallagher 2006

2.5 RBV Perspective on Open Innovation and Innovation Performance

There are several strategic management theories to help organisations plan and allocate resources and achieve their goals (David 2005; Hashim 2005). The most notable and relevant is the resource-based view (RBV), which encompasses several areas and is commonly used in various research areas (Mahoney & Pandian 1992). In fact, it has been hailed as the most influential strategic framework to study the value of resources in various fields (Ferlie et al. 2015; Galbraith 2005; Ziesemer 2013).

The origins of resource-based approaches can be traced to Selznick (1957), Penrose (1959), Stigler (1961), Chandler (1962) and Williamson (1975). Later, a number of scholars made noteworthy contributions to the development of RBV and extended RBV theories (Son et al. 2014), but Barney's (1991) article 'Firm Resources and Sustained Competitive Advantage' created awareness among scholars about the applicability of RBV theory in various circumstances, which led to the widespread use of the RBV theory.

Scholars have presented different definitions, but all highlight the value of resources and capabilities in improving firm performance (Barney 1991). Resources and capabilities differ; Grant (1991), for instance, categorised resources into tangible, intangible and skills-based resources, while Wernerfelt (1984) categorised them into attractive and non-attractive.

Akio (2005) assessed RBV from a dynamic point of view to address insufficiencies, and incorporated the entrepreneurial viewpoint to develop a framework for an RBV of strategic management. RBV has been used for understanding the role of internal factors that can lay a foundation for a collaborative environment and facilitate externalities, which allows the absorption of knowledge spill-overs caused by the other firms, leading to innovation. In fact, scholars have explained the role of internal firm capabilities and environmental factors (Galbraith & Kazanjian 1986; Prahalad & Hamel 1990) in offering competitive advantage (Porter 1990). Hence, several studies have adopted the RBV to estimate the value of internal resources in creating capabilities and to improve firm's competitive advantage (Wade & Hulland 2004). A review of the literature on the empirical application of RBV and findings is summarised in Table 2.6.

Table 2.6: Empirical Studies of Open Innovation from the RBV Perspective

Reference	Method	Finding	Limitation
Bogers, Bekkers & Granstrand 2012	Literature review	An organisation's difficult-to-imitate resources can be used to exploit resource complementarities	Lack of empirical evidence
Costello et al. 2011	Longitudinal study of innovation management in Irish subsidiaries involving 29 open interviews	Unique knowledge is critical for innovation	This study was limited to Irish subsidiaries and the results many not be generalized
Torkkeli, Kock & Salmi 2009	Literature review	Propositions: Organisations with complementary assets will derive larger gains	Lack of empirical evidence

Barney (1991) suggests that organisations can achieve optimal returns when the resources are heterogeneously distributed across firms in the same industry. Moreover, firms with unique capabilities will have a sustainable advantage, as these capabilities are not easy to replicate (Wernerfelt 1984). This suggests a strong relationship between the resources firms retain and overall performance. Continuing with this logic, it can be asserted that organisations need to have access to unique resources beyond their boundaries. In fact, RBV identifies various motives for collaborative innovation (Mowery, Oxley & Silverman 1996).

In summary, the RBV provides a theoretical basis for linking access to unique resources to innovation and collaborative innovation, the basis for OI. In addition, OI offers insights into the use of RBV in relation to achieving competitive advantage by utilising the rare and unique resources (West & Bogers 2017). In this context, organisations tend to participate in collaborative innovation "to aggregate, share, or exchange valuable resources with other firms when these resources cannot be efficiently obtained through exchanges or mergers/acquisitions" (Das & Teng 2000, p. 37). Thus, the RBV perspective is relevant to the study of OI.

Organisations can benefit from both tangible and intangible resources to improve their performance in the form of innovative products, services and processes (Atuahene-Gima & Murray 2007). With changes in the business environment, the value creation mechanism has begun to shift from tangible resources to intangible resources, such as knowledge, creativity and innovation (Kor & Mesko 2013; Surroca et al. 2010).

According to Wernerfelt (1984), a firm is comprised of distinct assets and capabilities. The RBV assumes that a firm's capacity to acquire unique resources and control them can improve performance (Wade & Hulland 2004). The RBV perspective attempts to explain how internal conditions, resources and capabilities offer benefits from the acquisition of resources (Barney 1991; Eisenhardt & Martin 2000; Wernerfelt 1984). The RBV suggests that firms can gain a competitive advantage by attracting and utilising superior resources. These resources include "all assets, capabilities includes all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness" (Akio 2005, p. 129; Barney 1991; Daft 1983). However, resources are different from capabilities (Amit & Schoemaker 1993), therefore there is a need to provide clarity about the role they play in supporting the overall innovation performance (Kraaijenbrink, Spender & Groen 2010; Priem and Butler 2001). A review of the literature on the empirical application of the RBV is summarised in Table 2.7.

Table 2.7: Empirical Studies of Innovation Performance from the RBV Perspective

Reference	Method	Independent variable	Dependant variable	Finding	Limitation
Kamasak 2015	Survey of 194 organisations	Innovation strategy and technological capabilities	Innovation performance	Relationship between innovation performance and resource base	Findings need further replication, explanation and generalization
Laosirihongthong, Prajogo & Adebanjo 2014	A survey of 218 Thai organisations	Internal resource and network resource	Product and process innovation	Organisational resources determine innovation performance	Applicability of results to other countries may be dependant on the level of innovation development and the national culture
Zhang et al. 2009	A survey of 635 Chinese organisations	R&D capability	The no. of patents owned and the no. of patent applications	Relevance between capabilities and performance	Lack of generalizability

Earlier studies focussed on the role of knowledge in innovation (Bierly & Chakrabarti 1996; DeCarolis & Deeds 1999). For instance, Barney (1991) noted that a firm's competitive advantage depends on unique resource capabilities and that internal resources such as organisational processes, assets, knowledge capabilities and information can offer competitive advantage. Several studies have shown that these capabilities play a major role in innovation and strengthen the firm's goal of achieving better performance (Ainuddin et al. 2007). Rouse and Daellenbach (2002) explain that the organisation's resources are the key determinants of innovation performance. Felin & Hesterly (2007) and Wernerfelt (1984) highlight the importance of innovation and the link between innovation performance and the use of knowledge within the context of the RBV. A cross-industry study conducted by Palacios, Gil and Garrigos (2009) in Spain revealed the positive impact of resources on innovation performance.

In summary, the RBV theory examines the sources of firm performance (Amit & Schoemaker 1993; Barney et al. 2011; Michalisin, Smith & Kline 1997), and the role of internal resources in innovation performance. The theory provides valuable insights regarding the factors that influence innovation performance of firms. Therefore, this study aims to explore the key drivers of innovation that lead to improved innovation performance within the context of the RBV of the firm.

2.6 Relational View of Open Innovation and Innovation Performance

Dyer and Singh (1998) proposed the Relational View (RV) as a way to understand firm networks and their contribution to achieving competitive advantage. An organisation's network consists of customers, government regulation bodies, suppliers and other partners. RV concentrates on specific networks as the unit of analysis, such as unique resources including sharable knowledge, complementary assets and collaboration mechanisms, which are challenging for rivals to emulate.

While the RBV emphasises that firms need to maintain unique resources, the RV highlights the need for sharing these resources with other firms to improve innovation. Relationships among organisations are based on mutual interest, to allow exchange of knowledge (Mesquita, Anand & Brush 2008). These relationships play a significant role in promoting knowledge flows and the emergence of OI.

Business networks between firms allow establishment of communication channels (Jaworski & Kohli 1993). The RV highlights the common benefits firms can enjoy individually while maintaining alliances (Lavie 2006). Its main focus is on value creation through strategic alliances (Khanna, Gulati & Nohria 1998). It incorporates the views of RBV and transaction cost economics to suggest that relational rents can be produced through the adoption of appropriate strategic alliances and control mechanisms that permit knowledge flows between firms (Appleyard 1996; Hamel 1991).

Based on the proposition that firms use diverse methods to allow flow of knowledge, including predefined structures and coordination mechanisms through the use of technologies (Garcia-Morales, Bolivar-Ramos & Martin-Rojas 2014), Dyer and Singh (1998) studied interorganisational relationships to observe the role of network routines and processes in gaining competitive advantage, and suggested that relational rents can be generated through meaningful investment in relation to specific assets. Table 2.8 presents empirical studies on OI from the RV perspective.

Table 2.8: Empirical Studies of Open Innovation from the RV Perspective

Reference	Method	Independent variable	Dependant variable	Finding	Limitation
Castaldi, Kate & Barber 2011	Exploratory study – Interviews of 12 Chief Purchasing Officers in the Netherlands	Strategic purchasing	Innovation	Supplier involvement, quality of purchasing function and purchasing integration supports innovation	The systematic mapping of contingent factors can be challenging
Lenart-Gansiniec 2016	Literature review	Relational capital	OI	Interdependencies between relational capital and OI	Lack of empirical evidence
Gesing et al. 2015	Cross-industry survey of 2,502 German firms	Partner variety and collaboration governance	Collaborative innovation	Evidence of interaction effect between firms' internal R&D intensity and their engagement in innovation collaborations	Innovation collaborations are dependent on partner types, governance models and innovation objectives

Walker et al. (2013) successfully used relational theory to elucidate barriers and enablers for collaborative procurement. Their study revealed that partnering and managing relationships with other firms can be enablers in the collaborative procurement process. The RV highlights the significance of collaboration and sharing (Dyer & Singh 1998). When firms decide to collaborate, knowing and valuing each other will motivate knowledge sharing (Borgatti & Cross 2003; Reficco et al. 2018).

Scholars have highlighted the importance of external knowledge for innovation development (Darroch & McNaughton 2002); For example, Wang and Li-Ying (2015) studied how technological resources acquired from a software vendor can generate subsequent rents relating to innovation through the collaboration of different sets of partners. Kobayashi (2013) used the Toyota case to study how the RV can help achieve competitive advantage. His findings revealed that firms that are geographically co-located with unique resources have a high chance of gaining competitive advantage. A similar study by Dobrzykowski, Callaway and Voderembse (2015) suggests that relational theory can be useful in addressing challenges relating to translation of innovation into performance improvement. These deliberations form a strong basis for identification of relationships between the RV and OI.

The RV is an integrated approach, which looks at the role of interactions between the firm and its partners to explain the strategic opportunities that can be attained at low risk and cost (Son et al. 2014).

Firms are dynamic in nature because of constant competition (Priem & Butler 2001), and it is important to expand networks (Son et al. 2014) to achieve innovation performance. The innovation performance of organisations can be defined as efficiency and effectiveness in innovation activities (Song & Parry 1997), which is determined by process innovation, product innovation, service innovation and number of patents. Organisations with intense relationships with other organisations and share knowledge to achieve high reciprocal benefits (Dyer & Singh 1998). Table 2.9 presents empirical studies on innovation performance from the RV perspective.

Table 2.9: Empirical Studies on Innovation Performance from the RV Perspective

Reference	Method	Independent variable	Dependant variable	Finding	Limitation
Zhu, Zhong & Mei 2013	Hypotheses development	IT-enabled relational capabilities	Innovation performance	IT-enabled relational capabilities positively influence innovation performance	The proposed research model is not tested
Castaldi, Kate & Barber 2011	Exploratory study – Interviews of 12 Chief Purchasing Officers in the Netherlands	Strategic purchasing	Innovation performance	Supplier involvement, quality of purchasing function and purchasing integration support innovation	The systematic mapping of contingent factors can be challenging
Thompson & Heron 2006	A survey of R&D employees in 429 science and technology based firms	Relational quality	Innovation performance	Affective commitment leads to knowledge sharing, which is positively related to innovation performance	The focus is on one form of identity (organisation) and the role of other forms of identity (profession, department and workgroup) is not known

The RV provides a valuable basis for the study of innovation performance. Over the last two decades, the RV has been used widely by researchers to study the importance of acquiring costly-to-copy resources (Hart 1995), the benefits of interconnected firms (Eisenhardt & Schoonhoven 1996), the value of unique resources (Coleman, Cotei &

Farhat 2013; Costa, Cool & Dierickx 2013; Newbert 2008), the importance of sharing unique resources with other firms (Lavie 2006) and their relevance to innovation performance (Laosirihongthong, Prajogo & Adebanjo 2014). Ahuja, Yang and Shankar (2010) suggest that network relationships and collaboration activities among organisations lead to innovation performance.

OI occurs between organisations and other stakeholders who share knowledge to improve processes and co-develop products and services in loosely coupled networks (Palacios-Marqués, Merigo & Soto-Acosta 2015). The RV suggests that organisations can achieve innovation success by combining distinctive resources and participating in collaborative activities (Dyer & Singh 1998). In summary, the RV complements the RBV by supporting knowledge sharing across organisational boundaries through strategic alliances to improve innovation performance.

2.7 Absorptive Capacity in the Context of Open Innovation and Innovation Performance

OI and the organisation's capacity to absorb external knowledge are vital for innovation management. Absorptive Capacity (AC) is the organisation's capacity to exploit external knowledge, which is critical to improving innovation capabilities (Cohen & Levinthal 1990). It is an important characteristic for improving innovation capabilities and achieving competitive advantage (Lane, Koka & Pathak 2006; Zahra & George 2002).

Cohen and Levinthal (1990) argue that commonalities such as shared understanding in a given field help firms to identify, assimilate and utilise knowledge to meet their innovation needs. Roberts et al. (2012) suggest that accumulation of external knowledge supports internal innovation mechanisms and capabilities (Bharadwaj, Bharadwaj & Bendoly 2007; Tanriverdi 2006), which can be strengthened further through the management of networks with other firms spanning a firm's boundaries (Jansen, van den Bosch, & Volberda 2005; Jaworski & Kohli 1993).

The theoretical framework of AC proposed by Lane, Koka and Pathak (2006) suggests that internal knowledge resources and capabilities, long-term plans and networks facilitating flow of knowledge influence a firm's ability to absorb external knowledge. The RV proposed by Dyer and Singh explains that networks improve a firm's AC by facilitating exchange of knowledge. Empirical evidence also suggests that organisations in an established environment tend to adopt AC processes to promote innovation (Lavie, Stettner & Tushman 2010; Levinthal & March 1993). Volberda, Foss and Lyles (2010) points out the importance of goal clarity in enhancing knowledge transfer in relation to AC. Table 2.10 presents empirical studies on OI from the AC perspective.

Table 2.10: Empirical Studies on Open Innovation from the AC Perspective

Reference	Method	Independent variable	Dependant variable	Finding	Limitation
Ahn et al. 2016	A survey of 66 Korean firms	Openness and OI-related capacities	Firm performance	Interrelations between openness, OI capacities and firm performance	Lack of generalizability due to analytical tools and data collection method
Feniser, Lungu & Bilbao 2017	A survey of 118 Alba SMEs that implemented OI programs	Exploration learning, transformational learning and exploitational learning	OI	Interdependence between AC and innovation	Results are solely based on managerial perspective on OI and the AC of organisations.
Naqshbandi & Kamel 2017	A survey of 270 respondents from banking, public services, the airlines industry and telecommunications sectors in the UAE	Integrative culture and hierarchy culture	AC	Organisational culture of internal integration and external adaptation engages more in OI	Cross-sectional data may not be suitable for testing casual models Lack of generalizability due to a limited geographic focus

Zahra and George (2002) list four dimensions—acquisition, assimilation, transformation and exploitation—to explain how knowledge can be utilised. Conceptually, there are similarities with information processing theory; however, AC looks at an individual level, whereas the other focusses on the firm level (Vega, Gutierrez-Gracia & Lucio 2007). Lane, Koka and Pathak. (2006) believe that AC is crucial for innovation as it supports the use of external knowledge.

The conceptual models developed around AC analyse in detail the factors influencing a firm's AC (Vega, Gutierrez-Gracia & Lucio 2007). Zahra and George (2002) suggest that developing and managing AC can ensure long-term survival and success. Firms tend to cooperate with each other when the perceived benefits are mutual (Cohen & Levinthal 1990).

Table 2.11: Empirical Studies on Innovation Performance from the AC Perspective

Reference	Method	Independent variable	Dependant variable	Finding	Limitation
Ahn et al. 2016	A survey of 66 Korean firms	Absorptive and desorptive capacities	Organisational performance	Significant interrelations between openness, OI capacities and firm performance	Lack of generalizability due to analytical tools and data collection method
Kim, Kim & Foss 2016	A framework and propositions for future research	-	-	Practicing open and closed inbound innovation repeatedly and alternately develops AC and leads to innovative performance	Lack of explanation on building AC for inside-out processes
Lewandowska 2015	Literature review	-	-	Capabilities of external knowledge absorption for innovation performance and competitive advantage	Lacks empirical evidence
Rangus et al. 2015	A survey of 428 responses from Slovenian manufacturing and service firms	AC	Innovation performance	AC mediates the relationship between OI and innovation performance	Limitation with the open innovation measure Size distribution of the companies did not reflect the size distribution of the population

In summary, AC is an organisation's capacity to recognise and apply external knowledge and create monetary value from internal knowledge (Teece, Pisano & Shuen

1997). Literature devoted to AC highlights the benefits of external knowledge. Lane and Lubatkin (1998) explain that organisations can enhance the use of external knowledge through exploration and exploitation. In this context, organisations need to improve internal AC, as OI has an impact on an organisation's capability to search and source external knowledge and commercialise internal knowledge (Roberts et al. 2012; Lane, Koka & Pathak 2006). Table 2.11 presents empirical studies on innovation performance from the AC perspective.

AC is widely understood as the ability to absorb external knowledge (Cohen & Levinthal 1990). Zahra and George (2002) suggest that the exploitation of external knowledge leads to the development and refinement of outcomes. Later, Todorova and Durisin (2007) expanded on Cohen and Levinthal's definition to include acquisition and transformation in AC.

The OI model suggests the use of external knowledge and sale of internal knowledge to enrich internal innovation (Chesbrough et al. 2006, p. 2). Cohen and Levinthal (1990) suggest that an organisation's knowledge (external) absorption capacity has a significant positive impact on its innovation performance. They suggest that AC is associated with not only absorbing external knowledge, but integrating, embracing and commercialising it. Ahammad and Glaister (2011) agree that there is a strong relationship between knowledge transfer and organisational innovation performance.

The AC theory has been widely tested; for example, Iyengar, Sweeney and Montealegre (2015) used AC theory to gain insight and establish the role of information technology in organisational learning. Tzokas et al. (2015) developed a model to highlight the interactive nature of AC and examine the role of AC in transforming external knowledge into innovation performance. Junni and Sarala (2013) studied contextual (national cultural differences), individual (employee withdrawal) and organisational design (integration process communication and knowledge processing system) antecedents using data on Finnish acquisitions.

The concept of AC depends on the efforts and activities of organisations. Mangematin and Nesta (1999) found that organisations with a higher AC are able to use external knowledge proficiently compared with organisations with a lower AC. Zahra and George (2002) conceptualised AC as a dynamic capability.

The importance of AC in the context of innovation performance has been examined by various scholars (Junni & Sarala 2013; Iyengar, Sweeney & Montealegre 2015; Tzokas et al. 2015). Previous studies show that organisations need to have AC to benefit from inbound and outbound innovation processes and achieve innovation performance. An organisation's inbound and outbound OI activities coupled with AC not only influence its capacity to absorb external knowledge, but support its ability to integrate this with internal knowledge to transform processes, products and services and achieve competences.

2.8 Cluster Theory (CT) in the Context of Open Innovation and Innovation Performance

The word 'cluster' is a much-used word introduced by Michael Porter in his book 'The Competitive Advantage of Nations' in the 1990s to explain the behaviour of co-located firms in geographical proximity in achieving competitive advantage (Porter 1998). Porter's research into clusters and competition caught the attention of many researchers and government organisations as it helped gain a new perspective in relation to accessibility to knowledge resources through co-location of firms (Porter 2006, 1998, 1990).

The research on clusters dates back to the early 19th century, when similar behaviour was referred to as 'agglomeration' (Marshall 1920). According to Marshall (1920), a cluster consists of several firms from the same industry co-locating in a well-defined geographic location to provide economic benefits. Morosini (2004) viewed clusters as socioeconomic entities in a specific geographic location; whilst Djamila, Ratiba and Oumelkheir (2015) viewed clustering as a strategy to consolidate interdependent companies into a large business conglomerate.

Doeringer and Terkla (1995) defined clusters as geographically co-located firms with a similar business nature and interests. Rosenfield (1997) explains clusters as a concentration of firms with collaboration and cooperation interests, while maintaining competitive advantage through the exchange of ideas, business transactions and establishing communication channels. Porter (1998, p.78) described clusters as a ‘geographic concentration of companies and institutions in a particular field’. Porter’s view is that geographical proximity, networks and flow of information between the firms and stakeholders are vital for productivity, innovation and competitiveness (Porter 1998). The organisations in a cluster share common characteristics such as geographic co-location, business relationships between firms and similarities in resources, products, expertise and technologies (Nie & Sun 2014). Few scholars view clusters as regional innovation systems (Nie & Sun 2014) as they enable relationships among organisations and exchange of resources (Brusco 1992; Enright 1996; Sammarra & Biggiero 2001). Rosenfeld (1995) has a similar opinion that clusters offer co-learning, access to expertise and improvement of innovation capabilities. Earlier studies suggest that major innovations are the result of interactions and collaborations between firms. They also show that firms in an isolated environment are rarely innovative and the majority of innovations are the result of interactions (Carlson & Wilmot 2006; Porter 1998). Audretsch and Feldman (1996) suggest that innovation performance can be attributed to an organisation’s geographic location.

According to Dyer and Singh (1998), the RV approach will be beneficial only when there is value for co-creation, however, Kobayashi (2014) suggests that organisations need to be geographically close to proactively share knowledge with other organisations and participate in value co-creation. Whereas, Granovetter’s (1982, 1973) study into the influence of geographic distance between firms suggest firms that are separated in socially distant regions tend to have weaker ties, while co-located firms are able to maintain stronger ties with other firms and facilitate knowledge flows (Hansen & Serin 2010).

Research into the antecedents of AC by Volberda, Foss & Lyles (2010) suggests the need to study the impact of environmental conditions because of their influencing role in knowledge transfer. Cohen and Levinthal (1990) argue that firms adjust to the environment and absorb knowledge for continuous improvement, but D’Souza and Kulkarni (2015) state that a hurdle rate for AC in a dynamic multi-firm environment determines a firm’s survival rate. Studies that explore the knowledge transfer in clusters suggest that competitiveness of an organisation is dependent on its ability to access information in the surrounding environment to support internal innovation (Beijerse 2000; Chesbrough 2006, 2003; Karlsen et al. 2003).

A number of academic works emphasise the importance of clusters in facilitating access to new knowledge. Cluster theory (CT) promotes the idea of enhancing interactions and knowledge exchange, while the OI model is built on the principles of interaction among organisations and exchange of knowledge (Chesbrough 2003). Empirical evidence suggests that clusters improve knowledge transfer and innovation performance. The review identified that OI is interaction and resource intensive and geographic proximity enhances OI. In summary, geographic proximity of organisations has relevance to OI and innovation performance. A review of the literature on the empirical application of cluster theory is summarised in Table 2.12.

Table 2.12: Empirical Studies on Open Innovation and Innovation Performance from the Cluster Theory Perspective

Reference	Method	Independent variable(s)	Dependant variable(s)	Finding(s)	Limitation
Huang & Rice 2013	Secondary data of 3,468 (2,297 clustered and 1,171 non-clustered) firms from EU and non-EU countries	Geographic location	OI Innovation performance	Inter-firm networking improves innovation performance Regional clusters support unrestricted knowledge transfer between cluster-based firms, which positively affects innovation performance	Simplification of the sources of explicit and tacit knowledge
Giusti, Alberti & Belfanti 2017	Structured interviews of employees from 147 Italian and international organisations	Collaboration, knowledge networks and knowledge leaks	OI Knowledge acquisition	Organisations engaging in OI networks benefit from absorbing knowledge from cluster ecosystems	Lack of in-depth refinement of the concept of knowledge leak
Salvador, Montagna & Marcolin 2013	Literature review of OI trends		OI	A path dependence approach has influenced organisation OI implementation	Not supported by empirical evidence
Terstriep & Luthje 2009	Online surveys from company managers of the two clusters comprise 505 cluster members from Germany (325) and Switzerland (180) including firms, research organisation and public bodies	Cluster-internal interaction and cluster-external interaction Cluster-orientation Relational embeddedness AC	Innovation performance Innovation success Firm performance	Firm relational embeddedness in cluster-internal and -external innovation partnerships significantly enhances innovative success, which positive affects firm performance	Smaller sample size Relationships between the latent exogenous and endogenous variable should be accepted with caution
Sarvan et al. 2011	Interviews of managers from 31 licensed yacht building firms in Turkey	Degree of clustering Relational capital and intellectual capital Innovativeness & innovation resources Information sharing networks	Innovation performance Business performance	Innovation performance is dependent on the institutional context	The sample size was too small

2.9 Overview of RBV, RV, AC and CT Theories and Measures of Open Innovation and Innovation Performance

The implication of open innovation model is that firms need to shift from traditional closed innovation models to combine both internal and external knowledge to generate value, as well as commercialise internal knowledge (Chesbrough 2006). However, value creation in an organisation is dependent on the valuable and rare resources it owns (Barney 1991). While the RBV suggests ownership on unique resources, the notion of open innovation is also linked to interconnectedness of organisations, as interconnectedness enables alliances and collaborative innovation. The RV provides a relational perspective on how organisations can enable both inward and outward knowledge flows to bring-in new knowledge and share its resources with other organisations (West 2014). Based on RBV and RV theories, five constructs: degree of openness, direct stakeholder engagement, indirect stakeholder engagement, innovation practices and knowledge spill-overs are developed to measure open innovation and innovation performance. The absorptive capacity is the organisation's capability to absorb and embed external knowledge into internal innovation processes (Cohen & Levinthal 1990). As absorptive capacity enables organisations to accumulate new knowledge to improve innovation performance, a construct 'absorptive capacity' has been developed to study the mediating effect of absorptive capacity in between inbound open innovation and innovation performance. The cluster theory highlights the importance of geographic proximity in enhancing collaborations and knowledge exchange among firms which are critical for OI (Huang & Rice 2013; Porter 1998). Based on the cluster theory, a multi-group analysis is conducted in chapter 7 (section 7.4) to examine the role of geographic proximity on OI and innovation performance. The research model (figure 3.1) presented in chapter 3 details the constructs derived and their relevance to OI and innovation performance.

2.10 Summary

This chapter presented a literature review on OI, innovation performance and the relevance of the RBV, RV, AC and cluster theories. While, the RBV suggests that an organisation's non-substitutable resources determine the growth of the firm, the RV focusses on organisation's ability to share its resources with other organisations and access external resources through networks helps achieve sustained growth. While resource and network capabilities support knowledge flows, AC determines the organisation's capability to utilise external knowledge. Cluster theory highlights the value of co-location of organisations and knowledge flows that can positively affect innovation performance. Based on the literature review conducted in this chapter and the research background, problems, gaps and rationale presented in Chapter 1, the next chapter presents the research model and hypotheses.

Chapter 3: Development of the Theoretical Framework

3.1 Introduction

This chapter aims to develop a theoretical framework to establish the linkage between open innovation and innovation performance. Section 3.2 develops the research model and sets out hypotheses to establish the relationships between key constructs. The next two sections 3.3 and 3.4 introduce the constructs including degree of openness, stakeholder engagement (direct and indirect), innovation practices and knowledge spill-overs. Section 3.5 details open innovation constructs inbound innovation and outbound innovation, and innovation performance. Then, the interlined drivers that support open innovation are investigated in this conceptual model, i.e., the mediating effect of absorptive capacity. The role of clustering on open innovation and innovation performance are presented in sections 3.6 and 3.7. Section 3.8 provides a brief summary of the chapter.

3.2 The Development of the Theoretical Model

The literature presented in Chapter 2 identified two types of OI (inbound and outbound) and their role in achieving innovation performance. Earlier studies were limited to studying the benefits of OI in general; there are only a few studies highlighting the impact of geographical proximity and the need for AC to improve innovation performance. The proposed research model builds on (i) Chesbrough's (2012) OI model that considers an internal technology base and an external technology base as technical inputs leading to OI, and innovation performance as economic outputs, and (ii) Rangus et al. (2017) OI framework that considers the mediating effect of absorptive capacity in between OI and innovation performance. The proposed research model presented in Figure 3.1 explains how this study is positioned within the OI literature.

The research model of OI and innovation performance, presented in Figure 3.1 is based on a theoretical framework that integrates the resource-based view, relational view, absorptive capacity, and cluster theory. The research model includes the concepts of OI, innovation performance, absorptive capacity and geographic proximity. The relationships among these have been investigated to some extent, but in Korean (Ahn et al. 2016), Alba (Feniser, Lungu & Bilbao 2017), UAE (Naqshbandi & Kamel 2017), US (Zobel 2017) and European (Rangus, Drnovsek & Di Minins 2016; Rangus et al. 2017) contexts.

Table 3.1 details the concepts and their constructs in this research model. The six theorised relationships between constructs (degree of openness, direct and indirect stakeholder engagement), business models (OI practices and knowledge spill-overs), OI (inbound innovation and outbound innovation), economic outputs (innovation performance), absorptive capacity and geographic proximity are presented below. The open innovation model promotes both inward and outward knowledge flows. Literature (Cohen & Levinthal 1990; Lane, Koka & Pathak 2006; Zahra & George 2002; Ahn et al. 2016; Feniser, Lungu & Bilbao 2017; Naqshbndi & Kamel 2017) points out that the absorptive capacity mediates the relationship between inbound innovation and innovation performance. Earlier studies (Giusti, Alberti & Belfanti 2017; Huang & Rice 2013; Terstriep & Luthje 2009) have found the positive impact of geographic proximity on OI and innovation performance. Hence, the proposed research model tests the mediating role of absorptive capacity between inbound innovation and innovation performance, and the effect of geographic proximity on all aspects of OI and innovation performance.

Table 3.1: Constructs of the Proposed Research Model

Concept	Construct	Definition	Examples	Seminal authors
Technical Inputs	Degree of openness	Propensity to cooperate with other organisations	Willingness to search new partners Work with partners in new projects Allow them to access internal resources and technologies	Simard & West 2006; Van de Vrande et al. 2009; Barge-Gil 2010; Hung & Chiang 2010; Lazzarotti, Manzini & Pallegrini 2011; Rangus & Drnovsek 2013; Stanislawski & Lisowska 2015
	Stakeholder engagement (direct and indirect)	Level of engagement by both direct and indirect stakeholders in OI activities	Stakeholders are encouraged to work in new projects Stakeholders are provided with opportunities to work in innovation projects Feedback from the stakeholders are taken into consideration in R&D projects	Bourne & Walker 2005; Ayuso et al. 2006, 2011; Van de Vrande et al. 2009; Gould 2012; Rangus & Drnovsek 2013
	Innovation practices	Associated with efforts to harness OI in the organisation leading to high-quality performance	Practices that support and allow active participation from its stakeholders in innovation projects	Chesbrough 2003, 2004, 2006; Chesbrough & Crowther 2006; Felin & Zenger 2014; Huston & Sakkab 2006; Simard & West 2006; van de Vrande et al. 2009; Rangus & Drnovsek 2013
Business Models	Knowledge spill-overs	Flow of knowledge through interactions	Employees sharing their previous experience/knowledge with their colleagues Organisations allowing employees to share their knowledge with employees in other organisations Allowing employee participation in new projects to share their knowledge Commercial activities, joint	Dumont & Meeusen 2000; Chesbrough 2003, 2006; Vanhaverbeke 2006; Afua 2009; Rohrbeck et al. 2009; van de Vrande et al. 2009; Rangus & Drnovsek 2013; Montoro-Sa´nchez, Ortiz-de-Urbina-Criado & Mora-Valentı´n 2011

			ventures and strategic alliances with educational institutions and other organisations	
Open innovation	Inbound innovation	Exploration and exploitation of external resources for internal innovation	Exploration of new knowledge in the external environment Organisations' use of external knowledge from its stakeholders, educational institutions and research organisations for internal innovation	Chesbrough 2003; Laursen & Salter 2006; Morris, Kuratko & Covin 2008; Van de Vrande et al. 2009; Rangus & Drnovsek 2013; Sisodiya, Jhonson & Gregoire 2013; Greco, Grimaldi & Gricelli. 2015
	Outbound innovation	Organisation's expansion of OI processes outward with a monetary component	Improve profits through commercialisation of internal knowledge and multiplying it	Rigby & Zook 2002; Chesbrough 2006; Van de Vrande et al. 2009; Enkel, Gassman & Chesbrough. 2009; Dahlander & Gann, 2010; Busarovs 2013; Rangus & Drnovsek 2013; Greco, Grimaldi & Gricelli. 2015;
Economic Outputs	Innovation performance	The result of organisational active participation in OI activities. The ability to transform innovation inputs into outputs	Innovative performance shapes the development of new processes, products and services. Redesigned processes for organisational improvement Development of new products and services or modified products and services to fulfil customers' needs There is a relationship between OI activities and innovation performance	Laursen & Salter 2006; Van de Vrande et al. 2009; Jimenez-Jimenez & Sanz-Valle 2011; Yang 2012; Busarovs 2013; Rylkova & Chobotova 2014; Zizlavsky 2016

Absorptive capacity	Absorptive capacity	The organisation's capacity to absorb external knowledge to improve capabilities	Absorptive capacity is proven to improve OI capacities and performance New knowledge is absorbed into organisations processes New absorbed knowledge is used in R&D activities	Cohen & Levinthal 1990; Lane, Koka & Pathak 2006; Zahra & George 2002; Ahn et al. 2016; Feniser, Lungu & Bilbao 2017; Naqshbndi & Kamel 2017
Geographic proximity	Geographic proximity (clustering)	The physical distance between firms with similar business interests	Organisations located within a specific area Co-location of firms promotes inter-firm networking and facilitates knowledge flows to improve innovation performance	Boschma 2005a,b; Giusti, Alberti & Belfanti 2017; Huang & Rice 2013; Terstriep & Luthje 2009

The concept of OI refers to the use of purposive knowledge flows (inbound and outbound) to explore and exploit external knowledge to accelerate and commercialise internal innovations (Busarovs 2013; Chesbrough 2003; Dahlander & Gann, 2010; Enkel, Gassman & Chesbrough 2009; Greco, Grimaldi & Gricelli 2015; Van de Vrande et al. 2009). The knowledge base is a store of both internal and external knowledge available for use. The technical inputs domain is conceptualised through three constructs (degree of openness, direct stakeholder engagement and indirect stakeholder engagement) and the business models domain is conceptualised through two constructs (innovation practices and knowledge spill-overs). According to Chesbrough (2006, 2003), the technical inputs domain is concerned with the feasibility aspects such as willingness to cooperate and knowledge-sharing activities. This domain forms a basis for business models in the form of organisational practices to generate value and allow spill-overs for knowledge flows (Chesbrough & Rosenbloom 2002). The business model maps from the technical domain of inputs to OI and economic outputs, including value generated in the form of profits and performance.

Chesbrough (2006, 2003) explains that business models provide a linkage between the technical domain of inputs and the economic domain of outputs. The technical domain of inputs considers both internal and external technology bases as inputs. Figure 3.1 below outlines the research model and hypotheses. OI is conceptualised through the constructs inbound innovation and outbound innovation (Van de Vrande et al. 2009). The following section describes the relationship between the constructs in the research model and then presents the research hypotheses.

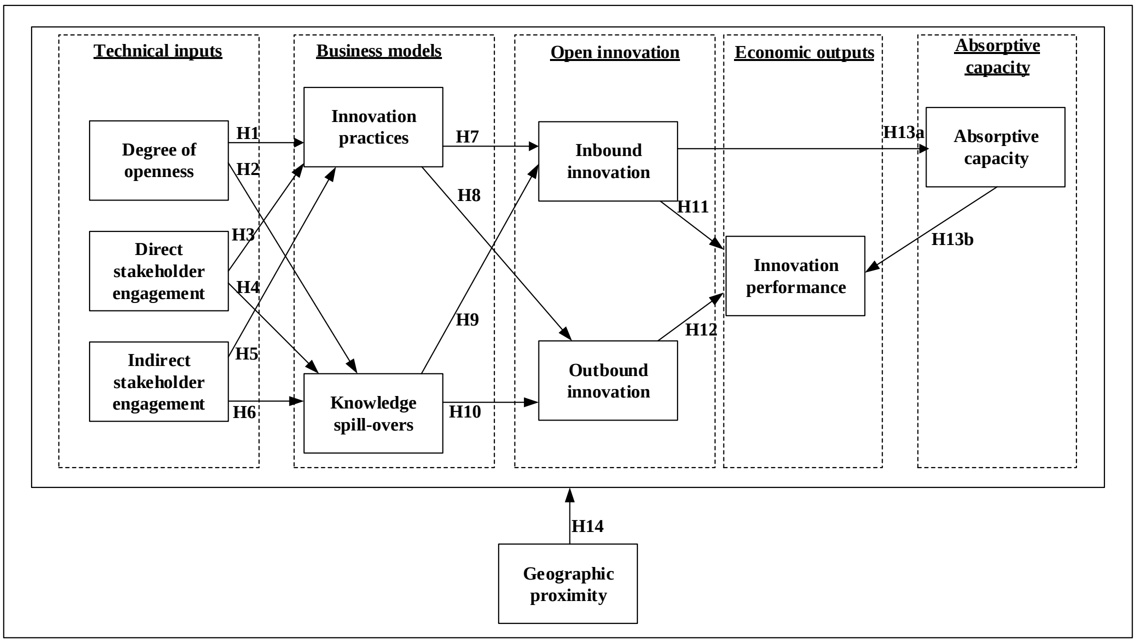

Figure 3.1: Theoretical Model and Hypotheses

Figure 3.1 describes the constructs of the research model and how these are related to each other. The following section investigates the relationship between OI constructs (inbound and outbound) and innovation performance. Then, the mediating effect of absorptive capacity and the role of geographic proximity in improving open innovation and innovation performance are detailed.

Innovation is the development of new processes, products and services by searching for and adopting new knowledge (Dosi et al. 1998), while, OI involves searching for and acquiring new knowledge from external sources to accelerate internal innovation (Chesbrough 2003). Earlier studies focussed on the benefits of innovation and its association with innovation performance. In response, researchers have focussed on innovation inputs such as processes (Chesbrough 2006, 2003; Chesbrough & Crowther 2006; Huston & Sakkab 2006; van de Vrande et al. 2009, 2006), openness (Barge-Gil 2010; Hung & Chiang 2010; Lazzarotti & Manzini 2011; Stanislawski & Lisowska 2015; Van de Vrande et al. 2009), stakeholder engagement (Ayuso et al. 2011; Ayuso et al. 2006; Bourne & Walker 2005; Gould 2012) and knowledge spill-overs (Afua 2009; Chesbrough 2006, 2003; Dumont & Meeusen 2000; Rohrbeck, Holzle & Gemunden 2009; van de Vrande et al. 2009; Vanhaverbeke 2006), and consequences including OI (Busarovs 2013; Dahlander & Gann 2010; Enkel, Gassman & Chesbrough 2009; Grimaldi & Gricelli 2015; Rigby & Zook 2002; Van de Vrande et al. 2009) and economic outputs such as innovation performance (Busarovs 2013; Jimenez-Jimenez & Sanz-Valle 2011; Laursen & Salter 2006; Van de Vrande et al. 2009; Yang 2012; Zizlavsky 2016).

The study is concerned with OI in IT clusters and innovation performance. The dependent variables are therefore OI and innovation performance, which are multidimensional constructs. Inbound and outbound innovations encompass R&D activities leading to new products, services and processes (Lee, Lee & Pennings 2001). Researchers have used different indicators to measure the innovation performance of an organisation. Of these, six stand out: IP rights and patents (Stuart 2000), process improvements (Lee, Lee & Pennings 2001), product and service innovation (Sisodia, Johnson & Gregoire 2013), investment in other organisations and collaboration activities (Gassmann & Enkel 2004).

To develop the theoretical model, this study draws from the strategic management theories presented in Chapter 2; in particular, Chesbrough (2006, 2003) and Van de Vrande et al.'s (2009) work on OI, which identify two main dimensions of OI—inbound and outbound—and clusters to theorise the relationship among constructs presented in Figure 3.1. The central argument is that the business model maps from the technical domain of inputs to OI and economic outputs such as inbound innovation, outbound innovation and innovation performance. Co-location within a cluster has a significant effect on OI and innovation performance as well as the relationship between the two. This argument is supported by recent studies (Ji et al. 2016; Sisodia, Johnson & Gregoire 2013; Wang, Chang & Shen 2015) on high-tech organisations that have found inbound and outbound innovation as key enablers to enhance innovation performance. Consistent with Chebrough's (2006, 2003) OI model, this study considers innovation as a system with specific inputs and outputs, as presented in Figure 3.1.

3.3 Technical Inputs

The technical inputs domain is concerned with the feasibility aspects associated with OI as cognitive filters operate in this domain. The technical inputs measured in this domain are the feasibility aspects such as degree of openness and direct and indirect stakeholder engagement (Chesbrough 2006, 2003). The following sections present the relationships between the constructs in technical inputs domain and the business models domain.

3.3.1 Degree of Openness

Over the last two decades, there has been a shift from closed innovation to OI, to propagate greater transparency in innovation processes (Barge-Gil 2010), increase reliance on external knowledge (Laursen & Salter 2006) and support research collaborations (Cassiman & Veugelers 2002). These new developments in innovation management have been associated with OI and are indicative of openness. This section investigates the concept of openness in the context of OI and its relevance to innovation practices.

Organisations possess significant resources, including skilled employees and unique knowledge (Rothwell & Dodgson 1991; Tether 2002), but conventionally, organisations have been comfortable with closed innovation (Barge-Gil 2010), as it allowed tight control over resources (Felin & Zenger 2014). While this approach offers short-term benefits, it may not offer long-term benefits (Herzog 2011). Further, closed innovation models do not fulfil the need for shorter innovation life cycles and reduced-time-to-market products and services (Enkel, Gassmann & Chesbrough 2009).

The traditional view of the relationship between internal innovation practices and organisational openness is based on Cohen and Levinthal's AC theory (1990, 1989), which suggests that existing knowledge determines the benefits achievable through external knowledge. According to Herzog (2011), intense global competition, technological complexities and a shortage of highly skilled research personnel are making closed innovation models unsustainable in almost every industry. Chesbrough (2006) predicts that closed innovation has a bleak future, because of the rising costs of technology development and shorter product life cycles, particularly in the IT industry, because of the large number of innovations around the world.

Chesbrough (2003) clarifies the benefits of moving towards business models that allow the use of both internal and external ideas in innovation projects to enhance innovation capabilities. OI is about connecting inbound ideas with outbound knowledge flows and utilising available technologies and skills (Su & Lee 2012). Chesbrough (2003) suggests that firms can benefit by controlling their R&D activities and intellectual capital. However, an organisation's ability to reach out to other organisations in the network allows them access to superior technologies (Gulati & Sytch 2007). Lazzarotti and Manzini (2011) point out that an organisation's openness and capability to acquire new knowledge are determined by their partner and innovation phase variety (Teirlinck & Spithoven 2008).

The degree of openness is the propensity to cooperate with other organisations (Freel & Robson 2017; Stanislawski & Lisowska 2015). It refers to both inward and outward orientation involving all transactions relating to knowledge sharing in the innovation area (Michelino et al. 2014). An organisation's innovation processes are influenced by its ability to cooperate and share unique knowledge across its network (Beraud, du Castel & Cormerais 2012). This construct is measured by the organisation's capability to access new knowledge, innovation strategies adopted to facilitate knowledge flows (Barge-Gil 2010), networks with capability to source new partners and maintain partner variety (Van de Vrande et al. 2009) and ability to obtain reliable support from partners (Lazzarotti & Manzini 2011).

The construct of openness consists of various layers (Freel & Robson 2017; Petrusson, Rosen & Thornblad 2010, p. 18). Han et al. (2012) explains that openness positively influences OI alliances. However, openness may vary with the level of control participants have over accessing and exploiting knowledge (Boudreau 2008; Petrusson, Rosen & Thornblad 2010, p. 18). A relevant body of knowledge on OI attempts to reveal the role of factors associated with an organisation's preparedness to improve openness in their innovation processes.

Earlier studies examined various perspectives on openness, including the direction of openness (Enkel, Gassman & Chesbrough 2009; Keupp & Gassmann 2009; Lichtenthaler & Ernst 2008), the range of partners (Enkel, Gassman & Chesbrough 2009; Keupp & Gassmann 2009; Laursen & Salter 2006), innovation network management (Pisano & Verganti 2008) and the level of integration among partners (van de Vrande et al. 2009). The literature also highlights that the availability of internal resources, R&D efforts, innovation portfolios, limited financial resources (Barge-Gil 2010; Bonaccorsi, Giannangeli & Rossi 2006; Harrison & Koski 2010; Henkel 2006) and the need to accelerate R&D activities (Alexy, Henkel & Wallin 2013; Chesbrough 2006; Chiaroni, Chiesa & Frattini 2011; Dobrev & Carroll 2003) motivate organisations to open up their innovation processes.

Although Chesbrough's (2006, 2003) OI model does not derive openness as a construct, it considers the importance of openness in enabling outside-in and inside-out knowledge flows. Previous studies (Simard & West 2006; Van de Vrande et al. 2009; Barge-Gil 2010; Hung & Chiang 2010; Lazzarotti, Manzini & Pallegrini 2011; Rangus & Drnovsek 2013; Stanislawski & Lisowska 2015) have acknowleged the role of openness in external knowledge acquisition. In fact, degree of openness is a well-established concept in the alliance and network literature. Adoption of openness in innovation practices leads to knowledge spill-overs through unplanned mechanisms (Roper, Vahter & Love 2013). Benefits of openness signifies its relevance to organisations' innovation practices. Therefore, it can be argued that an organisation's willingness to allow knowledge diffusion (spill-overs) and access external knowledge can be fulfilled by appropriate innovation practices. Hence, this study states the following two hypotheses:

H1: The degree of openness has a positive and significant relationship with innovation practices.

H2: The degree of openness has a positive and significant relationship with knowledge spill-overs.

3.3.2 Stakeholder Engagement (Direct and Indirect)

Stakeholders are either individuals or organisations who are impacted by the organisation's goals, policies and decisions (Freeman 1994). Stakeholder engagement is the level of engagement by both internal and external stakeholders in OI activities (Ayuso et al. 2011, 2006; Bourne & Walker 2005; Gould 2012). Stakeholders have a genuine interest in the organisation's processes, products and services. They play an important role in stimulating innovation and economic benefits (Owen & Goldberg 2010; Von Schomberg 2013). Tidd and Bessant (2013) point out that a number of businesses are recognising the potential benefits of social entrepreneurship, as it allows organisations to pursue both parallel and complementary trajectories for social value creation. Stakeholder engagement not only stimulates collaboration but also helps organisations to avoid conflicts and identify unique solutions when they arise.

For Freeman et al. (2010), there are various types of stakeholders. Direct stakeholders are entities that have a noticeable role in the organisation. Indirect stakeholders are those whose interests are either enhanced or threatened. Customers, employees and suppliers such as technology providers and government organisations are direct stakeholders (primary) as they define the business. Indirect stakeholders (secondary) are generally competitors, start-up companies and education providers (Freeman 1984).

Huizingh (2011) points out that the performance of OI is reliant on the choice of the right stakeholders. Freeman's (1984) initial work on stakeholder importance was strategic in nature as it focussed on value creation and profit maximisation through stakeholder engagement. Engagement allows processes of communication and relationship development (Waddock, Graves & Gorski 2000). Andriof and Waddock (2002) suggest that stakeholder engagement supports the development of collaboration and shared goals. However, it is organisational leadership that develops appropriate practices to facilitate interactions with external stakeholders (Maak 2007). In this context, stakeholder engagement can be the precursor for organisational practices aimed at involving stakeholders for the improvement of processes, products and services (Greenwood 2007). These organisational practices allow interaction among various stakeholders and promote knowledge sharing in both inward and outward directions (Gould 2012).

The OI model presented by Chesbrough (2003) highlights that organisations can achieve benefits by accessing external knowledge and combining this with internal knowledge. Later, van de Vrande et al. (2009) categorised OI into inbound (inward knowledge flows) and outbound (outward knowledge flows). Stakeholder engagement promotes deliberate interactions among stakeholders to facilitate knowledge flows. As knowledge flows are bidirectional, stakeholder engagement plays an important role in OI. Both stakeholder engagement and OI describe similar organisational processes, and tend to expand networks to reach other organisations to search and exploit external knowledge (Gould 2012). Although there are similarities between the two organisational processes, Gould (2012) believes that these are isolated from each other. To highlight the value of stakeholder engagement, it was incorporated into Chesbrough's (2003) OI model.

The integrated approach by Gould (2012) suggests organisations to adopt practices to support both inbound and outbound innovation. Inbound knowledge supports knowledge retention and internal innovation. Whereas, outbound innovation leads to knowledge spill-overs into networks. The literature points out that no single organisation possesses all the resources and knowledge required for innovation. In fact, Chesbrough's (2003) OI model reiterates the need to harness knowledge from external stakeholders and allow internal innovation and knowledge to spill-over, which could be important for stakeholders. In this context it can be argued that the stakeholder engagement can influence and change the direction of innovation as it supports retention and exploitation of knowledge. Thus, it is considered crucial for OI success. However, for OI to be operational, organisations need to adopt appropriate processes (Nonaka et al. 1994). The role of innovation practices for knowledge flows can be seen in the context of inbound and outbound innovation. Hence, the following hypotheses are offered:

> *H3: Direct stakeholders' engagement has a positive and significant relationship with innovation practices.*
> *H4: Direct stakeholders' engagement has a positive and significant relationship with knowledge spill-overs.*
> *H5: Indirect stakeholders' engagement has a positive and significant relationship with innovation practices.*
> *H6: Indirect stakeholders' engagement has a positive and significant relationship with knowledge spill-overs.*

3.4 Business Models

The business models domain maps from the technical inputs domain in the form of organisational practices to generate value and allow spill-overs for knowledge flows. It provides a linkage between technical inputs domain and economic outputs domain. The following sections present the relationships between the constructs in business models domain and OI constructs and economic outputs domain.

3.4.1 Innovation Practices

Collaboration among organisations is considered a critical activity in the innovation literature (Cheisa & Manzini 1998). In fact, there have been several studies on how collaboration facilitates knowledge flows and its influence on internal innovation (Clark & Fujimoto 1991; Eppinger 2001; Katz & Allen 1982; Trott & Hartmann 2009). The OI model proposed by Chesbrough (2003) also attempts to benefit from collaboration activities. In the light of value co-creation, it suggests organisations to extend innovation processes to stakeholders for new knowledge acquisition and allow spill-overs to be used by other organisations.

The shift from closed innovation models to OI is mainly because of increased costs of innovation and awareness of the benefits of collaborating and sharing resources. Chesbrough (2003) considers 'open innovation as a paradigm that assumes that firms can and should use external ideas, and internal and external paths to market, as the firms look to advance their technology'. Although there are several advantages with the OI model, there is very limited understanding on how innovation practices support organisations' OI efforts. Further, the adoption of an OI model requires significant changes to organisational innovation practices.

OI encompasses various forms of innovation processes and bridges the gap between closed and open business models (Laursen & Salter 2006). However, the development of OI is a complex process, requiring management of both inward and outward knowledge flows (Martinez-Conesa et al. 2017). It describes the need for processes towards innovation in terms of different OI activities. In this context, OI practices are the set of decisions made by managers for each knowledge supply through networking (Bellantuono, Pontrandolfo & Scozzi 2013; Huizingh 2011; Spithoven, Clarysse & Knockaert 2010; Van de Vrande et al. 2009). These practices help develop specific capabilities necessary for 'systematically performing knowledge exploration, retention, and exploitation inside and outside an organization's boundaries throughout the innovation process' (Lichtenthaler 2009). As OI is dependent on interorganisational linkages and exploration and exploitation of external knowledge, OI practices are critical in this context (Enkel, Grassmann & Chesbrough 2009).

Organisations may participate in several activities including sharing or selling knowledge or acquiring external knowledge or both (Chesbrough & Bogers 2014). Vergara and Otero (2015) point out the role of OI strategies in innovation performance. The theoretical foundation of OI suggests systematic exploration and exploitation of external knowledge and commercialising of internal innovations. Hence, the following hypotheses are offered:

H7: Innovation practices have a positive and significant relationship with inbound innovation.

H8: Innovation practices have a positive and significant relationship with outbound innovation

3.4.2 Knowledge Spill-overs

Knowledge management is widely recognised in the innovation literature as a critical approach to leverage to improve innovation performance (Githii 2014). The successful development and implementation of new processes, products and services is dependent on external knowledge. The knowledge, or intellectual capital, can be transported across organisational boundaries easily without a tariff; for example, the movement of skilled individuals leads to knowledge diffusion and innovation performance (Howell 2005).

Knowledge spill-overs are externalities caused by commercial activities (Dumont & Meeusen 2000), joint ventures and strategic alliances with educational institutions and other organisations (Afua 2009). Spill-overs consist of important knowledge that occur through interactions and exchanges among organisations (Verspagen 1997). These spill-overs benefit other organisations along the way (Griliches 1984) by allowing them to acquire critical knowledge (Dumont & Meeusen 2000). Scholars argue that this knowledge can be put to better use if the organisations have similarities in terms of products and services (Lovely & Popp 2008; Nemet 2012). Spill-overs through the demonstration effect take place when a domestic firm improves its productivity by simply observing nearby firms and copying their technology. Dechezleprte et al. (2011) also suggest that these knowledge flows can allow transfer of technologies. In particular, knowledge relating to technology, products, processes and management methods can help firms to imitate and improve performance (Glass & Saggi 1998, 2002b).

Knowledge spill-overs occur when an organisation benefits from the knowledge and technology developed by other organisations (Kafouros et al. 2008). It affects organisational processes, products and services (Howell 2005). The literature suggests organisations acquire new external knowledge to support innovation. The benefits of spill-overs can be maximised by adopting business models that acknowledge the existence of informal ties. The OI model contrasts the benefits of outbound flows of knowledge and technology. Chesbrough (2006, p. 9) states that 'enabling outward flows of knowledge and technology allows organisations to let technologies that lack clear path to market internally seek such a path externally', to reveal the potential benefits.

From an OI point of view, external knowledge spill-overs are potential resources, which need to be brought-in to support internal innovation (Cohen & Levinthal 1990). Every type of knowledge is important for innovation (Chesbrough 2006, 2003; Nemet 2012; Walz 1997). To facilitate knowledge diffusion, organisations allow independent collaborations to facilitate interaction among various stakeholders to achieve innovation goals, which leads to movement of knowledge across boundaries (Kafouros et al. 2008). Chesbrough (2003) also suggest adopting appropriate practices that promote outward knowledge flows to maximise economic benefits in the form of commercial applications. Therefore, it can be argued that OI is highly dependent on the interactions among organisations and knowledge flows. Based on the above argument, it is proposed that:

> *H9: Knowledge spill-overs have a positive and significant relationship with inbound innovation.*
> *H10: Knowledge spill-overs have a positive and significant relationship with outbound innovation.*

3.5 Open innovation and Economic Outputs

To assess whether OI and economic outputs measure variables of relevance to technical inputs, it is important to study correlations. Econometric techniques are used to determine the impact of inputs, specifically innovation performance, in relation to processes, products, services and intellectual property rights. The following sections present the relationships between inbound and outbound innovation and innovation performance.

3.5.1 Inbound Innovation

Inbound innovation refers to an organisation's use of external knowledge from stakeholders, educational institutions and research organisations for internal innovation (Chesbrough 2003; Greco, Grimaldi & Cricelli 2015; Laursen & Salter 2006; Morris, Kuratko & Covin 2008). Van de Vrande et al. (2009) explain that it is the outside-in process that allows access to external knowledge that is not available in-house. In fact, there has been significant research examining the benefits of external knowledge (Chesbrough 2003; Cui et al. 2015; Laursen & Salter 2006). Better access to resources determines the growth of the firm (Penrose 1959), improving performance and viability of a business in the long run (Sisodia, Johnson & Gregoire 2013). Access to external complementary resources is necessary to sustain competitive advantage (Teece & Pisano 1994). The knowledge gained from external sources can be decisive to organisations' innovation efforts (Laursen & Salter 2006), but these resources, as argued by Barney (1991), have to be valuable, rare and non-substitutable.

Inbound innovation is associated with collaborative networks. Organisations' inbound innovation practices include searching for and sourcing new technologies and external knowledge to improve existing processes, products and services (Chesbrough 2003; Greco, Grimaldi & Cricelli 2015; Laursen & Salter 2006; Morris, Kuratko & Covin 2008).

Chesbrough (2003) explains that collaboration activities with stakeholders support organisational efforts to improve the quality of products and services via sharing information and resources. A study on vertical and horizontal collaboration by Parida, Westerberg and Frishammar (2012) found collaboration was a key source of knowledge residing outside the organisation, which can be harnessed for internal innovation. Inbound innovation, therefore, reflects an organisation's use of available external knowledge from collaborators, educational institutions and research organisations, which provides the basis for internal innovation (Greco, Grimaldi & Cricelli 2015).

A study by Lichtenthaler (2009) found that OI helps to achieve a return on investments. The organisation's capability to search for and source external knowledge influences its innovation performance (Busarovs 2013; Van de Vrande, de Jong, Vanhaverbeke & de Rochemont 2009) as inbound innovation processes leverage external inputs for internal R&D (Sisodia, Johnson & Gregoire 2013). Earlier studies (Busarovs 2013; Chesbrough 2006, 2003; Van de Vrande et al. 2009) identified ways to improve an organisation's innovation performance through inbound innovation activities. To determine the effect of inbound innovation on innovation performance, the following hypothesis is developed to be tested:

> *H11: Inbound innovation has a positive and significant relationship with innovation performance.*

3.5.2 Outbound Innovation

Outbound innovation refers to an organisation's expansion of OI processes outward with a monetary component in the long run through commercialisation of internal inventions (Busarovs 2013). Enkel, Gassman and Chesbrough (2009) defined it as an inside-out process that promotes technology exploitation in the form of knowledge sharing or commercialisation of innovations. The OI model not only implies an accelerated form of internal innovation by importing new ideas but the exporting of proprietary technologies to generate income (Rigby & Zook 2002). Outbound innovation pertains to the external exploitation of internal knowledge such as patents or key knowledge resources (Greco, Grimaldi & Cricelli 2015) through commercialisation and licensing (Sisodia, Johnson & Gregoire 2013). Outbound innovation involves improving profits through commercialisation of internal knowledge and multiplying this knowledge by transferring it to the outside environment (Enkel, Gassmann & Chesbrough 2009).

Venturing, licensing and employee participation are critical to implementing an outbound strategy (Ahn, Minshall & Mortara 2015; Chesbrough 2006; Van de Vrande et al. 2009). Venturing involves opening a new business through incidental knowledge. Selling licenses, royalties and sharing knowledge with a monetary component are all part of outward licensing of IP rights. The participation of non-R&D employees in collaboration projects helps to leverage their ideas and knowledge (Van de Vrande et al.

2009). Outbound innovation activities are considered complementary to internal development as outward knowledge flows are proven to affect product performance and support internal innovation projects. This implies that there is a strong correlation between an organisation’s outbound innovation capabilities and its overall innovation performance (Yang 2012).

> *H12: Outbound innovation has a positive and significant relationship with innovation performance.*

3.6 Absorptive Capacity

AC is an organisation’s capability to identify, absorb and apply external knowledge to transform internal operations, products and services (Vanhaverbeke, van de Vrande & Cloodt 2008). It integrates new external knowledge into innovation processes (Arbussa & Coenders 2007).

OI is categorised into inbound (outside-in) and outbound (inside-out) knowledge flows (Van de Vrande et al. 2009). In the inbound process, knowledge is acquired from a number of external sources (Chesbrough & Crowther 2006; Enkel, Gassmann & Chesbrough 2009). To benefit from external knowledge and engage in the knowledge acquisition process, organisations need to develop their ‘absorptive capacity’ (Cohen & Levinthal 1990; Laursen & Salter 2006). Similar to the OI model, AC seeks to benefit from absorbing external knowledge. The organisation’s capabilities and resources allow a smooth integration of external knowledge into the organisation (Dahlander & Gann 2010; Spithoven, Clarysse & Knockaert 2010).

Desorptive capacity is the capability to benefit from internal knowledge in the form of licensing-out (Lewandowska 2015). Outbound innovation involves facilitating outward knowledge flows (Van de Vrande et al. 2009). Kirschbaum (2005) suggests that organisations can generate additional income by commercialising internal knowledge and technologies. A study conducted by Mo Ahn et al. (2013) also identifies a positive relationship between OI capacities and organisational performance.

In the outbound OI process, firms with a strong ‘desorptive capacity’ voluntarily disclose knowledge to less-informed economic agents (Lichtenthaler & Lichtenthaler

2009; Mortara & Minshall 2014; Van Der Meer 2007). In this regard, an organisation's knowledge management capacity not only mediates openness and performance but affects 'search' (inbound open innovation) and 'desorptive' capacity (outbound OI). Building on this, the following hypotheses are presented:

> *H13a: Inbound innovation has a positive and significant relationship with absorptive capacity.*
> *H13b: Absorptive capacity has a positive and significant relationship with innovation performance.*

3.7 Geographic Proximity

A geographic cluster is a group of related organisations in a geographical area with opportunities for innovation through collaboration and cooperation (Chesbrough 2006). An IT cluster is a group of inter-related IT companies that cooperate and compete within a geographic location (Belussi 1999). The impact of clustering on knowledge and technology transfer and innovativeness has become an important area for knowledge management researchers. Various cluster theories, including industrial districts (Marshall 1920), regional innovation systems (Nie & Sun 2014) and regional economies and clusters (Porter 1998, 2000), highlight the role of location in promoting innovation.

As clusters stimulate cooperation and collaboration among organisations within a cluster, organisations can promote purposive knowledge flows to overcome challenges associated with resource and budgetary constraints of R&D activities through partnerships on OI projects. Clusters create difficulties in terms of organisations keeping valuable technical knowledge within their boundaries, because the externalities caused by commercial activities with agents and informal relationships among employees from different organisations within the cluster enable the surrounding organisations to absorb knowledge to gain productivity without paying for it (Dumont & Meeusen 2000; Grossman & Helpman 1991).

Organisations can achieve dynamic capabilities through agglomeration economies, which enable development of new business networks and knowledge sharing among organisations in a cluster (Porter 2000). Clusters are the focal points of regional growth, which lay a foundation for the idea of collaborative processes to support OI

(Chesbrough 2006). Location theories suggest that social interactions between skilled people lead to new ideas. Limitations to internal R&D activities, proximity, networks and partnerships are the drivers for opening innovation activities (Theyel 2013). Thus, the co-location of organisations and a web of networks play a significant role in promoting innovation. This encourages firms to engage in strategic alliances to aggregate, share or exchange valuable resources (Das & Teng 2000). In turn, interorganisational linkages have a significant impact on innovation performance.

The major sources of knowledge spill-overs are external, and there are diverse knowledge sources in external surroundings. Spill-overs are likely to occur within the same cluster because of the similarities in products and services and applicability of technology and processes (Liu 2008). Relationships between organisations co-located within a geographic proximity are characteristic of vibrant and high-performing IT clusters (Hakansson & Snehota 1995). Bengtsson and Sölvell (2004) suggest that R&D-oriented organisations tend to perform better due to the competitive yet collaborative environment within a high-performing cluster. Diffusion of innovation to other organisations is more likely to be fostered in a clustered business environment where firms are interlinked and interdependent. As clusters facilitate interaction and increase collaborative opportunities for knowledge transfer, organisations within a cluster are expected to show higher innovation performance compared with the organisations outside the cluster. Hence, the following hypothesis is presented.

> *H14: Organisations within a cluster perform better in terms of OI and innovation performance than organisations outside the cluster.*

3.8 Summary

This chapter developed a conceptual framework for OI and its relevance to innovation performance. The research model consists of six theorised domains technical inputs (degree of openness, direct and indirect stakeholder engagement), business models (OI practices and knowledge spill-overs), OI (inbound innovation and outbound innovation), economic outputs (innovation performance), absorptive capacity and geographic proximity. The first part of this chapter detailed the conceptual framework, and then the concepts relating to the model were presented. The literature review identified significant relationships between the constructs presented in the research model. Based on the concepts brought together in the research model, the research hypotheses were stated. Chapter 4 presents the research methodology that lays the foundation to empirically examine the theoretical framework and test the research hypotheses stated in this chapter.

Chapter 4: Research Methodology

4.1 Introduction

The previous chapters provided the research background (Chapter 1), the concept of OI and innovation performance (Chapter 2) and the theoretical framework of the research (Chapter 3). This chapter outlines the methodology adopted to address the research questions and hypotheses. It also describes the research philosophies, research method and approaches considered appropriate for data collection and analysis for examining the hypothesised relationships of the constructs proposed in the research model. Section 4.2 provides research design. Then section 4.3 details three scientific philosophies—positivism, post-positivism and constructivism. Section 4.4 details quantitative and qualitative strategies of inquiry. Section 4.5 presents various research methods. Section 4.6 specifies domain of the construct. Section 4.7 provides sample of items for the constructs presented in the research model. Section 4.8 outlines pre-testing procedure. Section 4.9 details pilot test for assessing reliability and construct validity. Section 4.10 explains the data collection process. Section 4.11 provides a summary of the contents presented in this chapter.

4.2 Research Design

The overall design depicts linkages between the research problems and achievable outcomes. It involves making decisions relating to the type of data required and scientifically proven methods to analyse the collected data to address the research questions (Cresswell 2009). The research design logic varies depending on the nature of the research problem and the method adopted for analysis. Inefficient methods of data collection and analysis can compromise research and produce incorrect results (Bryman & Bell 2011). Hence, the research design needs careful planning to address the claims and detail the approaches of inquiry, data collection and analysis.

4.3 Research Philosophy

The philosophy of science focuses on questions relating to science and the scientific method. It attempts to clarify the role of science and asks about various issues including the difference between the theory and law of science, realism and anti-realism, and provides a scientific explanation and understanding on how and why science is done (Saunders, Lewis & Thornhill 2009). The research philosophy sheds light on the nature, applications and limitations of each logic. The three scientific philosophies—positivism, post-positivism and constructivism—can be used depending on their applicability and situation (Bryman & Bell 2011).

Ontology refers to investigation into reality and a clear description of the conceptualisation (Creswell 2009). It is a methodical version of existence in the real world, which can be explicitly represented to describe the relationships among various objects (Becker & Niehaves 2007). Philosophy has several sub-fields, including epistemology, which is concerned with the environment and extent of knowledge and observes the relationship between beliefs and reality. In other words, it attempts to offer support in obtaining relevant knowledge and interpret it to gain an in-depth understanding of the world (Khazanchi & Munkvold 2003). Its main emphasis is on human beings' interpretation of existing knowledge to clarify reality, and the main context is whether the social world can be studied using existing knowledge, principles and procedures. As noted above, different epistemological paradigms include positivism, post-positivism and constructivism (Bryman & Bell 2011).

According to Wisker (2008), positivism is based on the principle that human society resembles the natural world and is affected by fixed universal and permanent laws such as gravity. Therefore, it assumes that behaviour can be determined and there is a lesser scope for interpretation. In essence, it is associated with behaviourism and naturalism, and argues that knowledge and truth exist in so far as they can be proved. Therefore, positivists believe that 'there is a reality out there', which can be studied and understood (Persson 2010). Although the core theme may remain the same, constituent elements may vary between authors (Bryman & Bell 2011).

The positivistic paradigm is mainly concerned with testing hypotheses and utilising empirical methodologies taken from the scientific disciplines to observe phenomena.

Hypothesis testing is an example of a scientific method, which involves making a rough hypothesis based on observations from the available data (Berg 2007). The hypothesis provides an explanation of a 'possible correlation between multiple phenomena' (Wisker 2008). In general, a positivistic paradigm uses large specific and precise data samples. Because of its high reliability and accuracy, it is widely used in research in several disciplines, including economics, psychology, management and marketing studies (Wisker 2008). Although positivism is viewed as useful, there are several misconceptions about it (Persson 2010). Anti-positivists suggest that as individuals do not exist in isolation, it is necessary to understand the surrounding environment, such as the cultural and social setting (Kock, McQueen & Scott 1997). As a result, science has shifted to post-positivism, where stereotypes are no longer the core theme (Trochim 2006).

The post-positivistic paradigm is mainly concerned with generating theories based on the way individuals think and work rather than fixed laws. It is built on the belief that knowledge is based on individuals' understanding of the environment and the absolute truth can never be found. Therefore, there is always room for improvement (Bryman & Bell 2011). Manjikian (2013) agrees that post-positivism will not discover the truth, but helps to assemble the facts and draws conclusions based on the surrounding research environment. Ryan (2006) also believes that knowledge is socially constructed. However, some researchers believe that scientific reasoning resembles the reasoning process of individuals, and the only difference between these is degree. Trochim's (2006) view is that scientists adopt specific procedures to guarantee that findings are accurate and verifiable, whereas individuals, in general, neither adopt specific procedures nor strive to assure the validity of observations. As there is a possibility for bias in this approach, it is important for scientists to demonstrate patience, courage and honesty in judgement. 'Patience, honesty, courage, persistence, imagination, sympathy and self-discipline' are the key attributes for success (Ryan 2006). Post-positivism can be used to study human behaviour (Henderson 2011; Samdahl 1999) as it emphasises meanings under different social settings. Hamati-Ataya (2012) believes that knowledge is embedded in history, socioeconomic factors and beliefs, and therefore, argues the 'validity and universality of the present, as well as future knowing'. He also suggested that, to benefit from this approach, the main focus should be on what can be learned from observations rather than focussing on eliminating error, or how to 'embrace factual manifestation of ideology, interests and identity'.

Table 4.1: Characteristics of Research Paradigms

	Positivism	**Post-positivism**	**Constructivism**
Concept	Associated with behaviourism and naturalism (Persson 2010). Human society resembles the natural world (Wisker 2008), which can be studied and understood (Persson 2010)	Associated with reality and surrounding environment (Bryman & Bell 2011). Develops theories based on the way individuals think and work rather than fixed laws; absolute truth can never be found (Bryman & Bell 2011), but helps to assemble the facts and draws conclusions based on the surrounding research environment (Manjikian 2013)	Associated with specific issues and social settings (Masani 2001). It is based on individuals' experience of a specific issue and their social setting, because every human being is 'entitled to their own view of reality' (Masani 2001)
Benefits	High reliability and accuracy (Wisker 2008)	Helps to study human behaviour (Henderson 2011; Samdahl 1999)	Highly reliable and widely accepted in the education industry (Porcaro 2011)
Limitation	As individuals do not exist in isolation, surroundings should be considered, which can influence the outcome (Kock, McQueen & Scott 1997)	There is a possibility for bias in this approach (Ryan 2006)	If the construct becomes environment, then the impact of surrounding environment is ignored (Andrew 2004)

Constructivism is an ontological position in which the main concern is about the nature and influence of social entities (Bryman & Bell 2011). It opposes the view that social actors do not have any influence in pre-existing conditions, such as culture. It is founded on common beliefs that human beings build knowledge based on past experiences and also 'from relationships between things, people and events' (Wisker 2008), as individuals make sense of their surroundings based on their background and other social settings. For example, people in a specific geographical location may have a common understanding and perception (culture); however, these perceptions may change over a period of time because their personal experiences lead to subsequent changes (evolution). Constructionism believes that the basic generation of meaning is completely based on individuals' experience of a specific issue and their social setting. This can also be considered a problem because every human being is 'entitled to their own view of reality' (Masani 2001). Andrew (2004) pointed out that when the construction becomes an environment, it is likely that the effect of the surrounding environment is ignored. Social–cultural constructivism works on the principles that individuals create knowledge through interactions with peers who are more knowledgeable. As a result, this approach is widely adopted in research in the education industry (Porcaro 2011) to improve teaching and learning practices.

From Table 4.1, it can be inferred that each of these three scientific philosophies are applicable in different research environments. While positivism believes that the absolute truth exists and can be understood through scientific methods, the post-positivist approach considers that the absolute truth cannot be found, however, facts can be assembled to enhance our understanding. Constructivism relies on the assumption that individuals create knowledge based on the surrounding environment and social setting. Each of these approaches offers benefits to researchers, however, it is important for researchers to choose the right approach to achieve their goals.

The positivist view has been widely adopted for research in information systems (Mingers 2001) because of its ability to evaluate the forces behind the outcome by dividing the research problem into manageable sets for hypothesis testing. It adopts scientific methods and develops a numeric measure of observations to conduct research (Creswell 2009). In addition, the current research is consistent with the principles of the positivist view. Thus, this research has adopted the positivist view.

4.4 Strategies of Inquiry

This refers to the method of choice adopted for the research. Research helps to discover or reveal facts to explore things that are not very well understood (Creswell 2009). Sometimes research is done to improve existing conditions (Bryman & Bell 2011). There are several classifications used to describe research methods, but the most common classification identifies two distinct methods: qualitative and quantitative (Myers 1997). The combination of quantitative and qualitative methods is called the mixed method, which is commonly adopted in modern research.

The quantitative method involves collection of numerical data through questionnaires and focuses on applying statistical methods to compile, analyse and describe the collected data (O'Leary 2005). The quantitative method was initially developed to investigate natural phenomena in the social sciences (Myers 1997). It tests hypotheses synthesised from theory to investigate causal relationships. The data obtained through quantitative data collection methods are easy to cleanse and interpret (Bryman & Bell 2011).

The qualitative approach adopts the idea of observing an individual’s experiences either through interviews or case studies. This method allows researchers to observe both social and cultural phenomena (Myers 1997). Case study research and action research, which focusses on studying people and their culture relating to customs, habits and mutual differences, are examples of this approach. The main idea is to conduct research without manipulating real-world situations, which enables researchers to gain insight into individuals’ experiences and perspectives, which can allow an in-depth understanding of the phenomenon (Creswell 2009). Data sources include onsite and offsite observations, questionnaires, interviews and the understanding of researchers (Myers 1997). The mixed method combines quantitative and qualitative methods for comprehensive evaluation of the problem and interpretation of the data (Creswell 2009).

Table 4.2: Characteristics of Quantitative and Qualitative Strategies of Inquiry

Characteristics	Quantitative	Qualitative
Research instrument	Structured	Naturalistic
Research goals	Clear	Clear
Reliability for repetition	High	Low
Sample size	Large	Small
Data collection method	Tools – survey questionnaire	Interviews
Data type	Numbers	Text
Outcomes	Based on causal relationships	Provides a realistic view
Limitations	Missing contextual details	Lack consistency

The choice of inquiry approach depends on the adopted research philosophy, aims and research questions (Hall & Howard 2008; Saunders, Lewis & Thornhill 2009). As stated in an earlier section, the current research is conducted based on the positivist view and employs a quantitative method to investigate the relationships between OI constructs and the OI capabilities of clusters. It tests hypotheses derived from a theoretical model, developed based on a literature review, to address the research questions presented in Chapter 1.

4.5 Research Methods

In general, academic research is conducted based on primary or secondary data. Primary research aims to identify unknown patterns, behaviour or facts for the first time. It adopts several techniques including field observations, interviews, study reports, focus group activities and surveys. Secondary research utilises material collected by others. Intellectual work such as books, journals and magazines can help researchers to understand what has already been studied and how existing knowledge can be used to support their current research work (Bryman & Bell 2011).

Quantitative data collection methods involve indiscriminate sampling and structured instruments to ensure responses are from a diverse population. There are alternatives for quantitative data collection methods, such as experiments, system generated/recorded data, observations and surveys.

Interviews are personal, and conducted through one-on-one sessions, either face to face or through the use of technology such as video conference or phone call. According to O'Leary (2005), interviews are a data collection method where a researcher seeks responses to open-ended questions on a specific topic or theme. As they rely on open-ended questions to record and observe, there may well be varying responses. Interviews are considered a very valuable research technique, as they help to understand individuals' perceptions, opinions and reasons for their behaviour or actions. In addition, the interviewer is able to seek clarification on certain responses provided by the interviewee. Moreover, conformance biases that are common in group work can be avoided. The interview process includes several steps such as identifying information needs, choosing the right method for an interview, preparing a layout and questions to ask, test and verify the layout, and conducting, transcribing, analysing and presenting findings (Rowley 2012). As this technique involves several steps, it consumes an enormous amount of time and demands careful planning. In these circumstances, a silent card system can be very useful because of the support it offers to the researcher by providing a reminder of the points to cover in the interview (Osteraker 2001). Structured interviews can stop both the researcher and the participant deviating from the topic, but can also limit the participant from expressing their opinions freely. However, this can be minimised by adopting a semi-structured interview process, which is suitable for theory testing and exploratory research (Sankar & Joes 2005).

Traditional interviews are done face to face; however, technologies allow researchers to conduct these through telephone or video conferencing facilities. Emailing can be an option to reach participants without physically travelling long distances. This approach can save on cost, but can also cause delays, which may lead to an interviewee losing interest in the research. Gentle reminders can help in reducing delays (Opdenakker 2006). Another issue that arises is the interviewer having difficulty clarifying participants' views or opinions. Approaches such as telephone interviews and video conferencing (video messenger) help researchers to reach wider geographic areas, particularly when these areas are not accessible because of regional conflicts, natural disasters, and other factors. The main limitation with telephone interviews is fewer social cues, as researcher and participant may not be able to see each other; however, this can be overcome with the use of technology such as video messenger facilities. Undoubtedly, interviews help researchers to collect individuals' opinions on a specific topic or issue, but it can be difficult to adopt this technique when a larger sample size is necessary. Focus groups can serve as an option in those circumstances (Bryman & Bell 2011).

Focus groups are a form of group interview or moderated discussion with a group of people around a specially formulated discussion guide (Stokes & Bergin 2006). The group members are randomly selected based on their relevance to the research. If the group members are selected based on their involvement in a specific situation or experience, these are called focussed interviews (Bryman & Bell 2011; Merton, Fiske & Kendall 1956). In focus groups, participants are encouraged by the moderator to interact with each other to express opinions. This technique is employed when creative thinking is needed and to gather responses from many participants collectively. Strategies such as visualisation, brainstorming, mind mapping, poetry, story and metaphor can be used to encourage creativity (O'Leary 2005).

Focus groups allow researchers to understand the phenomenon and construct meaning around it by observing the reasons behind it (Bryman & Bell 2011). Key steps in this process include determining the group size, defining the moderator's role, selecting participants, asking questions and recording responses (Bryman & Bell 2011; Shao, Chuang & Chen 2013). This technique is commonly used in market research, particularly to solicit information on customer knowledge and opinion about current products and on customer needs, which can be used to design new products and services. As in the other two approaches, it requires huge efforts and consumes significant time to organise focus groups and record participants' responses (Sutton & Arnold 2013). In addition, the researcher must pay attention to group size and cohesiveness, as larger groups can lead to sub-group formation, while a higher level of cohesiveness can lead to conformance bias (Robbins et al. 2014).

Bryman and Bell (2011) explain that 'surveys' are a cross-sectional design where data are collected to examine patterns and behaviour. This can be defined as a process of gathering information from a sample of people who are known to be representatives of a larger group, the 'target population'. Data are collected through a specially designed questionnaire, either on paper or online (O'Leary 2005). Results are analysed to identify patterns or trends. This technique is useful when research is conducted to measure or quantify specific attributes of a selected group of people. It also helps to make empirical observations about the relationship among variables (Cresswell 2009).

Table 4.3: Five Common Sources of Quantitative Survey Research Error

Error source	Description	Reasons
Population specification error (Heckman 1979)	This is due to incorrect selection of population for data collection	Self-selection by individuals Sample selection decisions by analysts or data processors
Sampling error (Assael & Keon 1982)	This is due to selection of multiple subjects with individual differences as a sample of the same population	Randomisation Probability
Selection error (Doherty 1994)	This is due to selection of a sample using the non-probability method	Non-probability method
Non-responsive error (Walle 2015)	The differences between the chosen sample and obtained sample	Poor administration of survey questionnaire
Measurement error (Walle 2015)	The difference between gathered data and required data by the researcher	Incorrect observation, measurement and recording of data

The survey process includes several steps: defining the sample size, identifying the representative sample, developing a questionnaire, distributing the questionnaire, collecting and analysing the data. Questionnaires can be distributed to a larger group in a shorter period of time. However, failure to identify the right sample can lead to sampling errors. In addition, there may be data collection or processing errors (Bryman

& Bell 2011). Many researchers suggest that a larger sample size can be a problem because of the time it consumes to distribute the survey questionnaires and analyse results (Creswell 2009; Bryman & Bell 2011). Common errors associated with quantitative survey research include population specification error, sampling error, selection error, non-responsive error and measurement error. Table 4.3 details five common sources of quantitative survey research error and associated reasons.

Using the quantitative survey research strategy, this research administered a survey questionnaire to collect data from organisations within and outside the Hyderabad IT cluster. While this method helps researchers to collect data, it is not free from errors. To minimise errors associated with the quantitative survey research method, a rigorous survey design process was adopted. Accordingly, a cross-sectional survey design was used to investigate the relevance of the co-location of IT organisations to OI and innovation performance, and the dimensions of OI. The survey includes quantitative instruments (e.g., semantic differential scale) to reflect various constructs such as 'degree of openness', 'direct stakeholder engagement', 'indirect stakeholder engagement', 'innovation practices', 'knowledge spill-overs', 'inbound innovation', 'outbound innovation', 'absorptive capacity' and 'innovation performance', as proposed in the research model.

Businesses commonly employ the survey questionnaire technique to understand the effectiveness of customer service and ways to improve it. Although it is commonly used, it is not an easy task to obtain the questionnaires completed by the relevant participants. LaRose and Tsai (2014), aiming to understand the role of cash incentives in improving questionnaire completion rates, found that cash incentives as little as 25 cents can be effective. A web-based online questionnaire is designed for this research to offer flexibility and convenience to participants.

Churchill (1979) suggested an eight-step process for developing measures. As depicted in Figure 4.1, this process includes specifying the domain construct, generating sample items, data collection, measure purification, data collection, reliability assessment, validation tests and norms development.

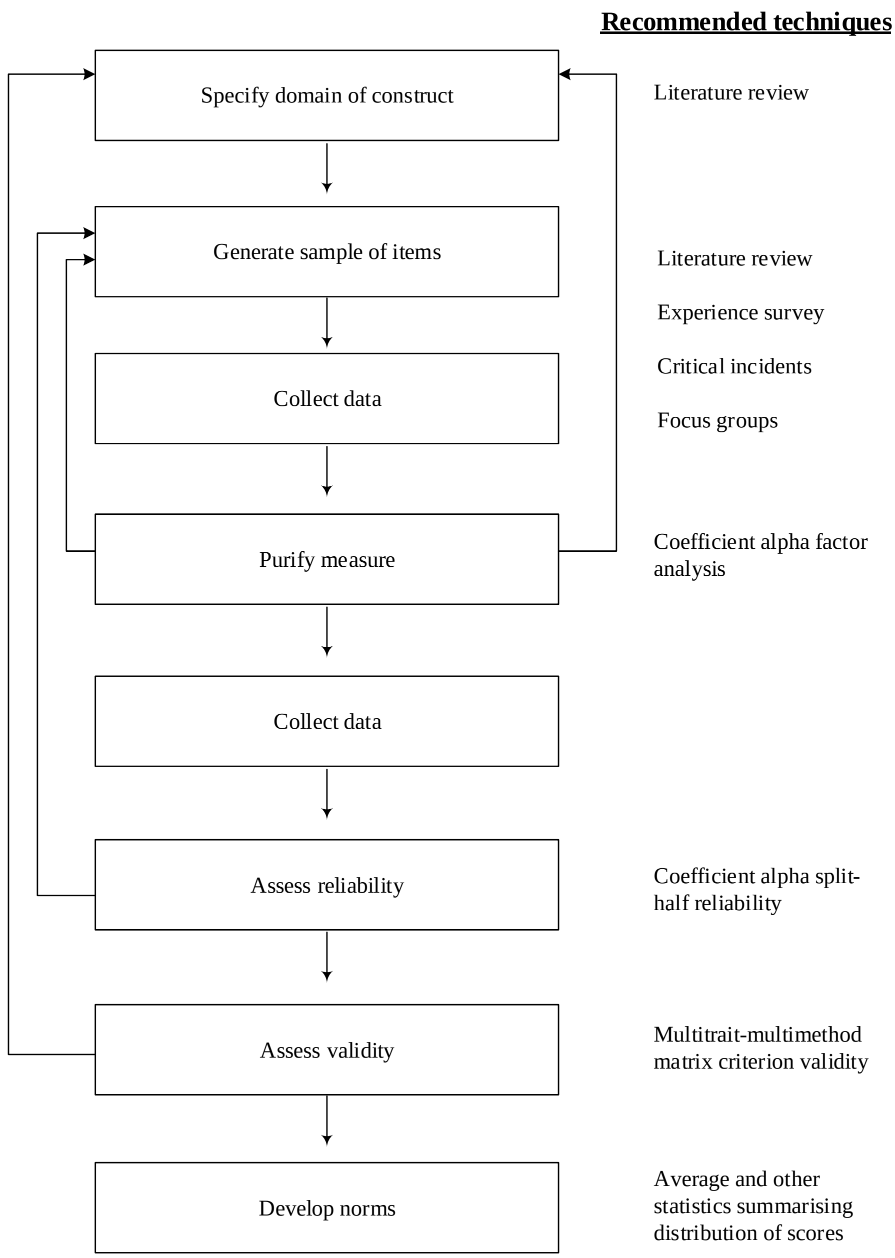

Figure 4.1: Suggested Procedure for Developing Better Measures (Churchill 1979)

4.6 Specify Domain of the Construct

The objective of this step is to define and clarify. According to Churchill (1979), the quality of measures depends on the procedures adopted in construct development. Thus, this step starts by selecting a concept and defining it to ensure relevance. Table 4.4 provides definitions for the conceptual model presented in Chapter 3.

Table 4.4: Specification of the Domain of the Construct

Concept	Construct	Definition	Examples	Seminal authors
Technical Inputs	Degree of openness	Propensity to cooperate with other organisations	Provides access to new partners and technologies	Simard & West 2006; Van de Vrande et al. 2009; Barge-Gil 2010; Hung & Chiang 2010; Lazzarotti, Manzini & Pallegrini 2011; Rangus & Drnovsek 2013; Stanislawski & Lisowska 2015
	Stakeholder engagement (direct and indirect)	Level of engagement by both direct and indirect stakeholders in OI activities	Facilitate knowledge flows	Bourne & Walker 2005; Ayuso et al. 2006, 2011; Van de Vrande et al. 2009; Gould 2012; Rangus & Drnovsek 2013
Business Models	Innovation practices	Associated with efforts to harness OI in the organisation leading to high-quality performance	Good practices include customer involvement, employee involvement and commercialisation of IP rights	Chesbrough 2003, 2004, 2006; Chesbrough & Crowther 2006; Felin & Zenger 2014; Huston & Sakkab 2006; Simard & West 2006; van de Vrande et al. 2009; Rangus & Drnovsek 2013
	Knowledge spill-overs	Flow of knowledge through interactions	Externalities caused by commercial activities, joint ventures and strategic alliances with educational institutions and other organisations	Dumont & Meeusen 2000; Chesbrough 2003, 2006; Vanhaverbeke 2006; Afua 2009; Rohrbeck et al. 2009; van de Vrande et al. 2009; Rangus & Drnovsek 2013; Montoro-Sa´nchez, Ortiz-de-Urbina-Criado & Mora-Valentı´n 2011
Open innovation	Inbound innovation	Exploration and exploitation of external resources for internal innovation	Organisations' use of external knowledge from its stakeholders, educational institutions and research organisations for internal innovation	Chesbrough 2003; Laursen & Salter 2006; Morris, Kuratko & Covin 2008; Van de Vrande et al. 2009; Rangus & Drnovsek 2013; Sisodiya, Jhonson & Gregoire 2013; Greco, Grimaldi & Gricelli. 2015
	Outbound innovation	Organisation's expansion of OI processes outward with a monetary component	Improve profits through commercialisation of internal knowledge and multiplying it	Rigby & Zook 2002; Chesbrough 2006; Van de Vrande et al. 2009; Enkel, Gassman & Chesbrough 2009; Dahlander & Gann,

				2010; Busarovs 2013; Rangus & Drnovsek 2013; Greco, Grimaldi & Gricelli. 2015;
Economic Outputs	Innovation performance	The result of an organisation's active participation in OI activities. The ability to transform innovation inputs into outputs	Innovative performance shapes the development of new processes, products and services. There is a relationship between OI activities and innovation performance	Laursen & Salter 2006; Van de Vrande et al. 2009; Jimenez-Jimenez & Sanz-Valle 2011; Yang 2012; Busarovs 2013; Rylkova & Chobotova 2014; Zizlavsky 2016
Absorptive capacity	Absorptive capacity	The organisation's capacity to absorb external knowledge to improve capabilities	Absorptive capacity is proven to improve OI capacities and performance	Cohen & Levinthal 1990; Lane, Koka & Pathak 2006; Zahra & George 2002; Ahn et al. 2016; Feniser, Lungu & Bilbao 2017; Naqshbndi & Kamel 2017
Geographic proximity	Geographic proximity (clustering)	The physical distance between firms with similar business interests	Co-location of firms promotes inter-firm networking and facilitates knowledge flows to improve innovation performance	Boschma 2005; Giusti, Alberti & Belfanti 2017; Huang & Rice 2013; Terstriep & Luthje 2009

4.7 Generate Sample of Items

An extensive literature review was conducted to understand OI dimensions and the role of clustering in facilitating a conducive environment for OI and innovation performance. Based on the comprehensive literature review, existing and validated research instruments, the survey questionnaire was developed. Items were developed to address a single issue and avoid 'double-barrelled' items (Harrison & McLaughlin 1993, 1991). An initial pool of items consisted of 65 items in total. The statements were made simple and meaningful to avoid confusion. There are no guiding rules for the number of items to be included in the questionnaire (Thurstone 1947); however, items are selected to ensure consistency and measure the concept being studied. The pooled instrument contained nine constructs:

- Degree of openness
- Direct stakeholder engagement
- Indirect stakeholder engagement
- Innovation practices
- Knowledge spill-overs
- Inbound innovation
- Outbound innovation
- Absorptive capacity
- Innovation performance

The initial pool of items was modified based on discussions with research experts to ensure relevancy between the constructs and items.

4.7.1 Degree of Openness

The items of the degree of openness construct were mainly derived from Aitken, Hanson and Harrison (1997), Simard and West (2006), Lazzarotti, Manzini and Pallegrini (2011), Hung and Chiang (2010), Rangus and Drnovsek (2013), Sisodiya, Jhonson and Gregoire (2013) and Parveen, Senin and Umar (2015). Two items (*'Our organisation manages its networks with other organisations through regular communications'* and *'Our organisation makes investments in other organisations to gain access to new knowledge/technology'*) relating to building networks and cooperation with partners were added based on discussion with experts (research supervisors) that highlighted that an organisation's willingness to build network capabilities supports its OI efforts. Moreover, cooperation is a critical aspect in facilitating knowledge flows (Simard & West 2006).

Table 4.5: Generated Items for Degree of Openness

Variable	Item	Source	Factor loading	Comment	Adjusted item
Access to new knowledge and technologies	Use of internal knowledge for innovation	Hung & Chiang 2010	Not reported	Adjusted	Our organisation maintains up-to-date knowledge about processes, products and services
Innovation strategies	Systematic ways of searching for external knowledge	Rangus & Drnovsek 2013	0.75	Adjusted	Our organisation's strategy focussed on open innovation, which encourages partnerships with other organisations
Building networks to support open innovation	Maintain interorganisational networks for OI	Simard & West 2006	Not reported	Own	Our organisation manages its networks with other organisations through regular communications
Partner variety	In the last five years you have collaborated with a wide variety of external actors	Lazzarotti, Manzini & Pallegrini 2011	>0.5	Adjusted	Our organisation has large number of partners in various industries
Awareness of new technologies and knowledge	Constantly scan the external environment for inputs such as technology, information, ideas and knowledge	Sisodiya, Jhonson & Gregoire 2013	>0.5	Adjusted	Our organisation has standard business processes to search and acquire external knowledge/technology
	We believe it is beneficial to determine systematic and formal ways of searching for external knowhow/technology	Rangus & Drnovsek 2013	0.83	Adjusted	Our organisation continuously searches for potential partners through trade shows and seminars
Investments	Knowledge spill-overs due to investments in other organisations	Aitken, Hanson & Harrison 1997	Not provided	Own	Our organisation makes investments in other organisations to gain access to new knowledge/technology
Approaches to solving problems	The degree to which an organisation values openness and responsiveness to new ideas, and a flexible approach to solving problems	Parveen, Senin & Umar 2015	Not provided	Own	Our organisation is willing to work with new partners in developing new products and services

The wording of the items was adjusted for consistency and readability. Table 4.5 lists the pooled items.

4.7.2 Stakeholder Engagement

The items of the stakeholder engagement construct were mainly derived from Rangus and Drnovsek (2013) and van de Vrande et al. (2009). The sample of items for employee involvement, customer involvement, external participation and outsourcing R&D constructs were adopted and validated in the previous studies. Three items (‘*Please rate how important “Technology providers” are in open innovation projects’, ‘Please rate how important “Competitors” are in open innovation projects’* and *‘Please rate how important “Government” is in open innovation projects’)* were added to gain an in-depth understanding of external stakeholder participation. Literature highlights technology providers for IT organisations and relevant government authorities are external stakeholders. Recent definitions of stakeholders include competitors. Therefore, these three items were selected through discussions with research experts. The wording of the items was adjusted for consistency, readability and to fit a 5-point Likert scale. Table 4.6 presents the pooled items and their factor loadings from previous research.

Table 4.6: Generated Items for Stakeholder Engagement

	Item	Source	Factor loading	Comment	Adjusted item
Employee involvement	Leveraging the knowledge and initiatives of employees who are not involved in R&D, for example by taking up suggestions, exempting them to implement ideas, or creating autonomous teams to realise innovations	Van de Vrade et al. 2009	0.72	Adjusted	Please rate how important “Employees” are in open innovation projects
Customer involvement	Directly involving customers in your innovation processes, for example by active market research to check their needs, or by developing products based on customers’ specifications or modifications of products similar like yours	Van de Vrade et al. 2009	0.59	Adjusted	Please rate how important “Customers” are in open innovation projects
Technology providers and government	Equity investments in new or established enterprises to gain access to their knowledge or to obtain others synergies	Van de Vrande et al. 2009	0.11	Own	Please rate how important “Technology providers” are in open innovation projects
				Own	Please rate how important “Government” is in open innovation projects
External participation	To acquire new knowhow/technology, we cooperate with knowledge institutions such as universities, faculties, institutes, laboratories	Rangus & Drnovsek 2013	0.75	Adjusted	Please rate how important “Education institutions and research organisations” are in open innovation projects
				Own	Please rate how important “Competitors” are in open innovation projects
	To acquire new knowhow/technology, we cooperate with high-tech start-up companies	Rangus & Drnovsek 2013	0.59	Adjusted	Please rate how important “Start-up companies” are in open innovation projects

4.7.3 Innovation Practices

Table 4.7 presents the pooled items and factor loadings from previous research. All the items except for ‘sale of IP rights for profit’ presented in this table are selected from previous studies. These items were utilised and validated by Rangus and Drnovsek

(2013) in their OI research. One item (*'Our organisation is supported by its partners in collaborative R&D projects'*) relating to sale of IP rights for profit was added based on the literature review conducted by Simard and West (2006) on concepts relating to OI. The wording of the items presented in this table was adjusted for consistency, readability and to fit a 5-point Likert scale.

Table 4.7: Generated Items for Innovation Practices

Original item	Source	Factor loading	Comment	Adjusted item
Open with customers	Chesbrough 2006	Not provided	Adjusted	Our organisation encourages cooperation with our customers to adopt new technologies
The innovation community is a network wherein anyone can propose problems and/ or offer solutions	Bellantuono, Pontrandolfo & Scozzi 2013	Not provided	Adjusted	Our customers participate in testing new products and services
We actively encourage communication among unrelated groups of employees in the company	Rangus & Drnovsek 2013	0.74	Adjusted	Our organisation encourages employees to acquire potentially beneficial technologies/ knowhow from external sources
We inform our employees about the importance of innovation to our business	Rangus & Drnovsek 2013	0.72	Adjusted	Our organisation informs us about the significance of open innovation to organisation's survival
We additionally award our employees if they bring external knowhow/technology that improves our products/services	Rangus & Drnovsek 2013	0.68	Adjusted	Our organisation rewards us for bringing in external technologies and knowledge to improve our products and services
When developing new ideas, we often consider the suggestions of employees not included in the research and development process	Rangus & Drnovsek 2013	0.65	Adjusted	Our organisation seeks feedback on proposed new products and services from employees not directly involved in R&D activities
Partner support is critical for knowledge inflows	Simard & West 2006	Not reported	Own	Our organisation is supported by its partners in collaborative R&D projects
Often bring in externally developed knowledge and technology to use in conjunction with our own R&D	Sisodiya, Jhonson & Gregoire 2013	>0.5	Adjusted	Our organisation facilitates access to external knowledge/technology to help develop new business opportunities to us

4.7.4 Knowledge Spill-Overs

Table 4.8 presents the pooled items from previous research. All the items except for 'R&D cooperation' presented in this table are selected from previous studies. The items were utilised and validated by Montoro-Sa´nchez, Ortiz-de-Urbina-Criado and Mora-Valentı´n (2011) in their innovation research on the effects of knowledge spill-overs on innovation and collaboration in science and technology parks, which used logistic binomial regressions to analyse various knowledge spill-overs types and their impact on innovations and the likelihood of interorganisational R&D collaboration. Montoro-Sa´nchez, Ortiz-de-Urbina-Criado and Mora-Valentı´n (2011) point out that spill-overs are the result of joint ventures and partnerships. Based on expert advice, three items (*'Our organisation considers external knowledge/technology to contribute to research and development of new products and services', 'Our organisation considers joint ventures/partnerships to create new knowledge/ technology' and 'Our organisation acquires knowledge/technology developed by institutions such as Universities, Professional bodies, R&D laboratories, etc.'*) reflecting the importance of knowledge spill-overs and the participants (supplier and customer) were included in the pool of items. The wording of the items presented in this table was adjusted for consistency, readability and to fit a 5-point Likert scale.

Table 4.8: Generated Items for Knowledge Spill-overs

Variable	Item	Source	Factor loading	Comment	Adjusted item
Importance	Importance of knowledge spill-overs as source of knowledge for firm innovation as the sum of the importance of all types of spill-overs	Montoro-Sa´nchez, Ortiz-de-Urbina-Criado & Mora-Valentı´n 2011	Not provided	Adjusted	Our organisation considers external knowledge/technology to contribute to research and development of new products and services
Supplier spill-overs Customer spill-overs	Importance of suppliers as source of knowledge for firm innovation Importance of customers as source of knowledge for firm innovation	Montoro-Sa´nchez, Ortiz-de-Urbina-Criado & Mora-Valentı´n 2011	Not provided	Adjusted	Our organisation considers joint ventures/partnerships to create new knowledge/ technology
Types of knowledge spill-overs	Importance of universities, innovation centres, and research institutions as sources of knowledge for firm innovation	Montoro-Sa´nchez, Ortiz-de-Urbina-Criado & Mora-Valentı´n 2011	Not provided	Adjusted	Our organisation acquires knowledge/technology developed by institutions such as Universities, Professional bodies, R&D laboratories, etc.
R&D cooperation	Our clients/end users are usually involved in the process of new product/ service development	Rangus & Drnovsek 2013	0.78	Adjusted	Our organisation involves customers in the development of new products and services
	Our products/services are usually developed in light of customer/client wishes and suggestions	Rangus & Drnovsek 2013	0.72	Adjusted	Our products and services are developed or redesigned based on customer feedback and their needs

4.7.5 Inbound Innovation

Table 4.9 presents the pooled items and their factor loadings from previous research. All the items for the inbound innovation construct are selected from previous studies. These items were utilised and validated by Rangus and Drnovsek (2013) and Sisodia, Johonson and Gregoire (2013) in their OI research. The wording of the items presented in this table was adjusted for consistency, readability and to fit a 5-point Likert scale.

Table 4.9: Generated Items for Inbound Innovation

Variable	Original item	Source	Factor loading	Comment	Adjusted item
Knowledge acquisition	We are willing to buy the intellectual property of other companies (e.g. patent, trademark) to support our internal development	Rangus & Drnovsek 2013	0.61	Adjusted	Our organisation is willing to buy other organisations IP rights such as trademarks and patents to support/ improve internal business processes
	To ensure successful development of new products/services, we usually buy the intellectual property of other companies	Rangus & Drnovsek 2013	0.78	Adjusted	Our organisation buys IP rights from others to develop new products and services
Knowledge exploration	Constantly scan the external environment for inputs such as technology, information, ideas, knowledge, etc.	Sisodiya, Jhonson & Gregoire 2013	>0.5	Adjusted	Our organisation upgrades existing technology to stay ahead of competitors

4.7.6 Outbound Innovation

To measure the construct of outbound innovation, the focus was on outward knowledge flows associated with venturing, exploitation of internal knowledge and commercialisation of IP rights. Two questions ('*Our organisation shares its knowledge with other organisations to create new knowledge/technology'* and *'Our organisation cooperates with other organisations and supports their projects to gain access to their knowledge/technology'*) on venturing was adopted from a study conducted by Rangus and Drnovsek (2013) on OI. Van de Vrande et al. (2009) suggest that in outbound OI, organisations voluntarily disclose internal knowledge, as they can exploit this by sharing it with other organisations. Chesbrough's (2006) OI model includes purposive outward knowledge flows in the form of commercialisation of IP rights. Based on the expert advice, two items (*'Our organisation provides open access to other organisations to use our internal knowledge with little or no cost'* and *'Our organisation sells or licenses its IP rights, patents, etc. to other organisations'*) were included to capture information relating to purposive outward knowledge flows. To explore willingness to commercialise intellectual property rights, two items ('*Our organisation sells or licenses its IP rights, patents, etc. to other organisations' and 'Our organisation prepares to sell Intellectual Property (IP) rights such as trademarks and* *patents for profit'*) were included. One item *('Our organisation is willing to enter into partnerships to introduce and promote new products and services'*) from Rangus and Drnovsek (2013) was included to understand the willingness to enter partnerships. The wording of the items presented in this table was adjusted for consistency, readability and to fit a 5-point Likert scale. Table 4.10 presents the pooled items for the outbound innovation construct from previous research.

Table 4.10: Generated Items for Outbound Innovation

Variable	Item	Source	Factor loading	Comment	Adjusted item
Venturing	When developing new activities related to the present operation of our company, we are willing to cooperate with the partners from the outside	Rangus & Drnovsek 2013	0.78	Adjusted	Our organisation shares its knowledge with other organisations to create new knowledge/ technology
				Adjusted	Our organisation cooperates with other organisations and supports their projects to gain access to their knowledge/ technology
In-house exploitation of knowledge	Sharing of resources with other organisations	Van de vrande et al. 2009	Not provided	Own	Our organisation provides open access to other organisations to use our internal knowledge with little or no cost
				Own	Our organisation shares its knowledge with competitors to absorb resulting knowledge/ technology
Commercialisation of IP rights	Selling or licensing technology to a third party	Chesbrough 2006	Not provided	Own	Our organisation sells or licenses its IP rights, patents, etc. to other organisations
				Own	Our organisation prepares to sell IP rights such as trademarks and patents for profit
Joint ventures	We believe that investing in a new joint venture could result in new knowhow/technology for our company	Rangus & Drnovsek 2013	0.64	Adjusted	Our organisation is willing to enter into partnerships to introduce and promote new products and services

4.7.7 Absorptive Capacity

Table 4.11 presents the pooled items for AC from previous research. All the items presented in this table are selected from previous studies. The items were utilised and validated by Rangus et al. (2015) in their research on OI. The wording of the items presented in this table was adjusted for consistency, readability and to fit a 5-point Likert scale. Table 4.11 presents the pooled items and factor loadings from previous research.

Table 4.11: Generated Items for Absorptive Capacity

Item	Source	Factor loading	Comment	Adjusted item
We have the capability to adapt acquired new knowledge to fit the firm’s development need	Rangus et al. 2015	0.85	Adjusted	Our organisation has the capability to utilise new knowledge to organisation’s benefit
We have the capability to develop new products/services by using assimilated new knowledge	Rangus et al. 2015	0.85	Adjusted	Our organisation has the capability to develop new products and services by using external knowledge
We have the capability to develop new applications by applying assimilated new knowledge	Rangus et al. 2015	0.85	Adjusted	Our organisation has the capability to develop new applications through absorbed new knowledge
We have the capability to find alternative uses of assimilated new knowledge	Rangus et al. 2015	0.89	Adjusted	Our organisation has the capability to develop alternative solutions by using external knowledge
We have the capability to fuse assimilated new knowledge with existing knowledge	Rangus et al. 2015	0.90	Adjusted	Our organisation has the capability to integrate new knowledge with existing knowledge
We have the capability to revise business procedures based on acquired new knowledge	Rangus et al. 2015	0.81	Adjusted	Our organisation has the capability to redesign existing business processes through absorbing new knowledge

4.7.8 Innovation Performance

Table 4.12 presents the pooled items for innovation performance from previous research. All the items for this construct are selected from previous studies. The items were utilised and validated by Jimenez-Jimenez and Sanz-Valle (2011) and Rylkova and Chobotova (2014). The items relating to financial performance were adopted from Kostopoulos et al. (2011). Based on expert advice, the wording of the items presented in this table was adjusted for consistency, readability and to fit a 5-point Likert scale. Table 4.12 below presents the pooled items and factor loadings from previous research.

Table 4.12: Generated Items for Innovation Performance

Variable	Item	Source	Factor loading	Comment	Adjusted item
Process innovation	Number of changes in process introduced	Jimenez-Jimenez & Sanz-Valle 2011	0.65	Adjusted	Please rate your organisation’s innovation performance for “processes” in the last three years
Product innovation	Number of new products introduced	Jimenez-Jimenez & Sanz-Valle 2011	0.67	Adjusted	Please rate your organisation’s innovation performance for “products” in the last three years
Service innovation	Number of new services introduced	Jimenez-Jimenez & Sanz-Valle 2011	0.67	Adjusted	Please rate your organisation’s innovation performance for “services” in the last three years
Acquired patents	Number of patents for a certain period	Rylkova & Chobotova 2014	Not provided	Adjusted	Please rate your organisation’s innovation performance for “intellectual property rights” in the last three years
Financial performance	Return on sales	Kostopoulos et al. 2011	Not provided	Adjusted	Please rate your organisation’s performance for “sales growth” in the last three years
Financial performance	Return on assets	Kostopoulos et al. 2011	Not provided	Adjusted	Please rate your organisation’s performance for “assets growth” in the last three years
Financial performance	Revenue growth	Kostopoulos et al. 2011	Not provided	Own	Please rate your organisation’s performance for “revenue growth” in the last three years

4.7.9 Geographic Proximity

The moderator variable can be a categorical variable. A moderator variable can be either qualitative or quantitative variable which affects the relation between an independent or a dependent variable (Baron & Kenny 1986). McKinnon (2011) points out that the moderating variables are included in a research study to understand the differences and similarities between the groups and to test whether an intervention has a similar effect across all the groups. Literature highlights the importance of studying the effect of moderating variables (Aguinis, Edwards & Bradley 2016; Namazi & Namazi 2016). According to McKinnon (2011) both the mediating and the moderating variables provide more information on how interventions work.

The fifth research question presented in section 1.5 attempts to reveal the effect of geographic proximity on open innovation and innovation performance. In order to study the impact of geographic proximity on open innovation constructs degree of openness, direct and indirect stakeholder engagement, innovation practices, knowledge spill-overs, inbound innovation and outbound innovation, absorptive capacity and innovation performance, this study considered geographic proximity as a moderating variable. Accordingly, in figure 3.1, an arrow is drawn from the moderating variable "geographic proximity" to the constructs measuring open innovation, innovation performance and absorptive capacity. As indicated in the research model, the effect of geographic proximity is tested using Kruskal-Wallis test and the results comparing the organisations within and outside the IT cluster are presented in section 7.5. The tables in section 7.5 present the mean scores for all the variables for organisations within and outside the cluster.

4.8 Pre-Testing Through Expert Evaluation

Pre-testing ensures content validity and sampling adequacy. One way to test validity is to report the origins of each of the items (Cavana, Delahaye & Sekaran 2001). To test the validity of the measures originating from previous studies in other nations, expert evaluation and a pilot test were conducted in the Indian context. A comprehensive evaluation was conducted by the subject experts (academics) from the Department of Business IT and Logistics at RMIT University. This evaluation process eliminated measurement errors and the difference between gathered data and required data by the researcher (Walle 2015). Feedback obtained in this step was used to remove redundant and double-barrelled items and to rephrase statements for clarity. Table 4.13 provides the list of questions deleted at the end of expert evaluation.

Table 4.13: Deleted Items for Each Construct

Construct	Item	Source	Adjusted item	Action taken
Degree of openness	The degree to which an organisation values openness and responsiveness to new ideas, and a flexible approach to solving problems	Parveen, Senin & Umar 2015	Our organisation is willing to work with new partners in developing new products and services	Redundant item deleted
Innovation practices	Open with customers	Chesbrough 2006	Our organisation encourages cooperation with our customers to adopt new technologies	Redundant item deleted
	The innovation community is a network wherein anyone can propose problems and/or offer solutions	Bellantuono, Pontrandolfo & Scozzi 2013	Our customers participate in testing new products and services	Item deleted as not all respondents would be familiar with innovation community concept
Absorptive capacity	We have the capability to develop new applications by applying assimilated new knowledge	Rangus et al. 2015	Our organisation has the capability to develop new applications through absorbed new knowledge	Redundant item deleted
Innovation performance (Financial performance)	Return on sales	Kostopoulos et al. 2011	Please rate your organisation's performance for "sales growth" in the last three years	Item deleted as the main focus is on measuring innovation performance
	Return on assets	Kostopoulos et al. 2011	Please rate your organisation's performance for "assets growth" in the last three years	Item deleted as the main focus is on measuring innovation performance
	Revenue growth	Kostopoulos et al. 2011	Please rate your organisation's performance for "revenue growth" in the last three years	Item deleted as the main focus is on measuring innovation performance

4.9 Pilot Test for Assessing Reliability and Construct Validity

The pilot test offers simulation of the actual test environment. Administration of the survey questionnaire to a sample of respondents from the target population or a population with resemblance to the target population can help assess reliability and determine whether measures correlate with other measures as anticipated (Cavana, Delahaye & Sekaran 2001).

The questionnaire obtained from the previous step was pilot tested with a sample of 25 respondents from organisations within and outside the Hyderabad IT cluster to assess reliability. The participants were provided with a web link to the survey questionnaire. On average, the participants took 20 minutes to complete the questionnaire. The participants provided valuable feedback relating to the number of questions and the time required to complete the questionnaire, with the majority feeling that it was lengthy and suggesting some of the similar questions be removed.

The results were deliberated and tested for inconsistencies to incorporate appropriate changes. The measurement instrument included unrelated and redundant items. It is important to refine these prior to administration of the survey questionnaire (Churchill 1979); thus, questions with closeness are removed. In addition, to achieve consistency and reliability of two or more construct indicators, Cronbach’s alpha (coefficient of internal consistency) was used (Field 2009) to assess the quality of the chosen measures (Churchill 1979).

The final survey questionnaire consists of 54 items. The initial ten questions pertained to characteristics of a participant’s organisation; the remaining questions aimed to collect data on degree of openness (seven questions), direct stakeholder engagement (four questions), indirect stakeholder engagement (three questions), innovation practices (six questions), knowledge spill-overs (five questions), inbound innovation (three questions), outbound innovation (seven questions), AC (five questions) and innovation performance (four questions). The research model measuring OI and innovation performance adopted for this research comprises nine constructs. Table 4.14 presents a list of items for each construct.

Table 4.14: Generated Items for Each Construct

Construct	Item
Degree of openness	Our organisation maintains up-to-date knowledge about processes, products and services.
	Our organisation upgrades existing technology to stay ahead of competitors.
	Our organisation’s strategy focussed on open innovation, which encourages partnerships with other organisations.
	Our organisation manages its networks with other organisations through regular communications.
	Our organisation has a large number of partners in various industries.
	Our organisation is supported by its partners in collaborative R&D projects.
Stakeholder engagement	Please rate how important “Employees” are in open innovation projects.
	Please rate how important “Customers” are in open innovation projects.
	Please rate how important “Technology providers” are in open innovation projects.
	Please rate how important “Competitors” are in open innovation projects.
	Please rate how important “Government” is in open innovation projects.
	Please rate how important “Education institutions and research organisations” are in open innovation projects.
	Please rate how important “Start-up companies” are in open innovation projects.
Innovation practices	Our organisation involves customers in the development of new products and services.
	Our products and services are developed or redesigned based on customer feedback and their needs.
	Our organisation encourages employees to acquire potentially beneficial technologies/knowhow from external sources.
	Our organisation informs us about the significance of open innovation to organisation’s survival.
	Our organisation rewards us for bringing in external technologies and knowledge to improve our products and services.
	Our organisation seeks feedback on proposed new products and services from employees not directly involved in R&D activities.
	Our organisation prepares to sell IP rights such as trademarks and patents for profit.
	Our organisation is willing to enter into partnerships to introduce and promote new products and services.
Knowledge spill-overs	Our organisation makes investments in other organisations to gain access to new knowledge/technology.
	Our organisation considers external knowledge/technology to contribute to research and development of new products and services.
	Our organisation considers joint ventures/partnerships to create new knowledge/ technology.
	Our organisation acquires knowledge/technology developed by institutions such as Universities, Professional bodies, R&D laboratories, etc.
	Our organisation cooperates with other organisations and supports their projects to gain access to their knowledge/technology.
	Our organisation shares its knowledge with competitors to absorb resulting knowledge/technology.

Inbound innovation	Our organisation facilitates access to external knowledge/technology to help develop new business opportunities to us.
	Our organisation is willing to buy other organisations IP rights such as trademarks and patents to support/ improve internal business processes.
	Our organisation buys IP rights from others to develop new products and services.
	Our organisation has standard business processes to search and acquire external knowledge/technology.
	Our organisation continuously searches for potential partners through trade shows and seminars.
Outbound Innovation	Our organisation shares its knowledge with other organisations to create new knowledge/technology.
	Our organisation provides open access to other organisations to use our internal knowledge with little or no cost.
	Our organisation sells or licenses its IP rights, patents, etc. to other organisations.
Absorptive capacity	Our organisation has the capability to utilise new knowledge to organisation's benefit.
	Our organisation has the capability to develop new products and services by using external knowledge.
	Our organisation has the capability to develop alternative solutions by using external knowledge.
	Our organisation has the capability to integrate new knowledge with existing knowledge.
	Our organisation has the capability to redesign existing business processes through absorbing new knowledge.
Innovation performance	Please rate your organisation's innovation performance for "processes" in the last three years.
	Please rate your organisation's innovation performance for "products" in the last three years.
	Please rate your organisation's innovation performance for "services" in the last three years.
	Please rate your organisation's innovation performance for "intellectual property rights" in the last three years.

4.10 Data Collection Process

4.10.1 Sampling Design

Section 4.5 presents various sampling frames commonly adopted for research. It details several primary data collection techniques including field observations, interviews, study reports, focus group activities and surveys (Bryman & Bell 2011). This study adopted online surveys for data collection as these allow researchers to gather information from a sample of people known to be representative of a larger group, the 'target population' (O'Leary 2005). According to Cresswell (2009), this technique is useful when research is conducted to measure or quantify specific attributes of a select group of people. It also helps to make empirical observations about the relationship among variables.

Using the quantitative survey research strategy, this research administered a survey questionnaire to collect data from organisations within and outside the Hyderabad IT cluster. While this method helps researchers to collect data, it is not free from errors. To minimise errors associated with the quantitative survey research method, a rigorous survey design process was adopted. A cross-sectional survey design was used to investigate the relevance of the co-location of IT organisations to OI and innovation performance. The survey includes quantitative instruments (e.g., semantic differential scale) to reflect on various constructs such as ‘degree of openness’, ‘direct stakeholder engagement’, ‘indirect stakeholder engagement’, ‘innovation practices’, ‘knowledge spill-overs’, ‘inbound innovation’, ‘outbound innovation’, ‘absorptive capacity’ and ‘innovation performance’, as proposed in the research model. Businesses commonly employ survey questionnaires to understand and improve the effectiveness of customer service. To improve the response rate, and offer flexibility and convenience to participants, a web-based online questionnaire was designed and distributed through email.

The sampling frame adopted for this research was based on the list of IT organisations within and outside the Hyderabad IT cluster and other Indian cities. The contact details of IT organisations in India were obtained from the Indian online recruitment website projobz (http://www.projobz.com/) and the online information provider fundoodata (http://www.fundoodata.com/). Both these companies update IT organisations’ data frequently and provide reliable information. Many businesses including HSBC, Google, Flipkart, Wipro and Mercedes-Benz rely on fundoodata for updated information relating to organisations in different industries. Both websites provide information of registered organisations in each Indian city, including their address, contact number and web links. At the time of accessing in July 2016, the list consisted of more than 1,200 organisations. The Google search engine also presented a list of IT organisations by the location, which was used as the population frame.

4.10.2 Participants

Information Technology (IT) refers to the hardware, software and networking components of an information system (Valacich & Schneider 2016). IT employees fall into one of the eight career clusters which include database development and administration, digital media, enterprise systems analysis and integration, network design and administration, programming/software engineering, technical support, technical writing and web development and administration. Regardless of the career cluster, the IT employees possess project management, task management, problem-solving, troubleshooting, cybersecurity and process skills (NWCET 2003).

The Indian Information Technology industry consists of services related to information technology and business process management. The Indian IT organisations are predominantly the service providers for both domestic and overseas organisations. According to IBEF (2019), India's IT industry grew to US$167 billion in 2018. The Indian IT sector consists of IT services, business process management, software products and engineering services and hardware. The Indian IT employees are the people with one or more skills in studying, designing, developing, implementing, managing and supporting information systems and its components.

The unit of interest is Indian IT organisations within and outside the Hyderabad IT cluster. However, the employee participation is vital for this study. Participants included the employees of IT organisations within and outside the Hyderabad IT cluster involved in critical roles such as leadership, sales, technology, consulting, corporate functions, process management, R&D, education and training. The participants have significant knowledge about their organisation and its approach to innovation. They are the key informants on the variables studied in this research.

4.10.3 Data Collection

In line with RMIT University's policies and procedures for data collection, an application with supporting documents including Participant Information and Consent Form (PICF) and Questionnaire was submitted to Business College Human Ethics Advisory Network (BCHEAN) for ethics approval. Appendix A presents the Participant Information and Consent Form. This invitation letter consists of information about the research project, who is involved in this research, investigator details, the purpose of this research, reasons for contacting the participants, participant rights, contact details in case of concern, security of the website and the steps adopted to ensure security of collected data. Appendix B presents the ethics approval for the data collection. This document outlines information about the research project, investigators and the terms of approval.

On receiving approval, the questionnaire was placed on a RMIT University recommended web-based survey tool ‘Qualtrics’. It is a secure application that allows the researcher to build, distribute and analyse online surveys. The web link to the online questionnaire was distributed to IT organisations within and outside the Hyderabad IT cluster. Participants were asked to share their knowledge about their organisation’s ability to access new knowledge, whether the knowledge is sourced internally or externally for their research and development activities and their organisation’s current practices relating to OI.

The questionnaire was pilot tested with a sample of 25 respondents to assess reliability. Sometimes, a measurement instrument may include unrelated items (Churchill 1979), and may warrant the refinement of these prior to confirmatory factor analysis (CFA). To achieve the consistency and reliability of two or more construct indicators, Cronbach’s alpha (coefficient of internal consistency) was used (Field 2009), which helped to assess the quality of the chosen variables (Churchill 1979). As the pilot study was proven to be reliable, the same questionnaire was used for the large-scale study.

4.10.4 Ethical Considerations

The participants were provided with information about how the collected data would be stored. The identifying information, such as participant names, staff id and personal details, were not collected to avoid adverse consequences and ensure participants’ privacy. Collected data was not associated with the respondent, so that no opinion was attributable. The responses to the survey were downloaded from the Qualtrics website and stored on the RMIT University server for analysis. Data are reported as aggregates, and no individual is identified.

4.10.5 Sample Size

A sample size is the number of survey responses that are considered for the study (Cavana, Delahyae & Sekaran 2001). Bryman and Bell (2007) explain that the research studies need to ensure that a sufficient sample size has been selected to meet the research purpose. Selecting a larger sample may dilute the effect and the results may have little significance. On the other hand, the results obtained with a smaller sample size may not offer conclusive evidence.

Literature suggests determining the minimum required returned sample size as incorrect sample size may fail to detect important effects and lead to insignificant effects (Bryman & Bell 2007; Hickey et al. 2018). Hence, it is important to achieve a right balance with sample size selection. Cavana, Delahyae and Sekaran (2001) provide guidelines to establish a minimum required sample size for research studies. They offer the following formula, which has been used to calculate the minimum required sample size.

$$Minimum\ required\ sample\ size\ (n)\ =\ \left(\frac{K * S}{E}\right)^2$$

Where K is the confidence level required, S is the standard deviation for the sample and E is the level of precision required or a margin of error. The confidence level can range from 0% to 100%. However, the level of significance (confidence level) accepted across most research studies is 90% - 95%. For the 90% confidence level, the applicable K value is 1.645. As the minimum sample size required is calculated prior to distributing the survey questionnaire, this study used 0.5 as S value to ensure that the sample size is large enough. The minimum confidence level considered for this study is 90 and the margin of error is +5%, which is equivalent to 0.05. Based on the formula presented earlier, the minimum required sample size is calculated as shown below.

$$Minimum\ required\ sample\ size\ (n)\ =\ \left(\frac{1.645 * 0.5}{0.05}\right)^2$$

$$n\ =\ \left(\frac{0.8225}{0.05}\right)^2$$

$$n\ =\ 271$$

Based on the formula suggested by Cavana, Delahyae and Sekaran (2001), the minimum required sample size is 271.

Cavana, Delahaye and Sekaran (2001) suggest considering the confidence level, sample standard deviation and the level of precision required for sample size selection. In contrast, Hair et al. (2010) suggest determining the minimum required sample size on the basis of type of analysis.

According to Hair et al. (2006), the estimation and interpretation of structural equation modelling (SEM) results depend on the sample size. Loehlin (1992) suggests a sample size of at least 200 for SEM with fewer than 15 indicators. This study aims to conduct exploratory factor analysis (EFA) using the statistical package for the social science (SPSS) and confirmatory factor analysis using AMOS, which suggest the sample size of 200 (MacCallum, Browne & Sugawara 1996). As there is no globally accepted rule of thumb relating to the sample size for a cluster analysis (Dolnicar 2002), Loehlin's suggestion was adopted to determine the sample size. In addition, to ensure goodness of fit, at least 271 responses were sought for the final study.

4.10.6 Data Analysis Procedures

The collected data were analysed using the SEM technique as this tests and estimates causal relations, and is proven to be reliable in studying the theory of planned behaviour and measuring the intention of the behaviour of interest (Hair et al. 2006). IBM SPSS and AMOS were used to deal with quantitative analysis from extant data. As shown in the conceptual model, the degree of openness, stakeholder engagement, innovation practices and knowledge spill-overs were proven to promote OI (inbound and outbound) and support innovation performance. CFA is used to gain an in-depth understanding of the relevance of these factors and overall impact (Field 2009). Finally, a structural model based on the research model presented in the previous chapter was tested.

4.11 Summary

This chapter detailed the research methodology adopted to measure the framework presented in Chapter 3. It explained the research design, various philosophies, strategies of inquiry and research methods. Based on Churchill's (1979) suggested procedure for developing better measures, the domain of the constructs was specified and a sample of items was generated. A detailed description was provided for the pool of items selected for each of the constructs in the research model and the pre-testing procedure, pilot test for assessing reliability and construct validity and data collection and analysis procedures were presented.

Chapter 5: Data Preparation for Analysis

5.1 Introduction

Once data have been collected through online questionnaires, the most important step in analysis is preparing the data for analysis (Cavana, Delhaye & Sekaran 2001). The data examination and preparation process is time consuming (Hair et al. 2010); however, this essential step allows researchers to address issues relating to missing data, identifying outliers and tests for assumptions. This chapter aims to describe data preparation procedures for analysing the collected data. This chapter is organised into nine sections. Section 5.2 outlines the steps adopted for data import and screening. Section 5.3 provides steps undertaken to edit the data and reasons for editing blank responses, coding and categorising the data. Section 5.4 describes the procedure undertaken for identifying outliers and the reasons for excluding outliers. Section 5.5 details the tests conducted on the normality of the sample and the approaches employed to address any abnormalities. Section 5.6 presents steps taken to estimate non-response bias. Section 5.7 presents tests adopted for common method bias. Section 5.8 presents the respondents' profile. Section 5.9 summarises the contents of this chapter.

5.2 Data Import and Data Screening

The data for this research was collected in India through the RMIT University-approved Qualtrics website. Qualtrics is an online data collection tool that allows researchers to place an invitation to participate in a research project, submit an online questionnaire, extract a web link to questionnaires for distribution and allow survey respondents to access it. The invitation to participate and the survey questionnaire are presented in the appendix. The web link to the questionnaire was distributed to 1,252 IT organisations in India during 2016–2018. Participants were asked to share their knowledge about their organisation's openness, direct and indirect stakeholder engagement, innovation practices, knowledge spill-overs, ability to explore and exploit external knowledge and organisation's innovation performance.

After an initial email to respondents in August 2016, a number of follow-up emails were sent to Indian IT organisations to encourage potential participants. As a result, a total of 495 responses were recorded. At the end of the data collection, the data had been imported as a CSV file to the RMIT server, where it will be stored securely for a period of five (5) years.

Hair et al. (2010) suggest examining data prior to multivariate techniques to gain an in-depth understanding of the characteristics of the data. Visual examination of data allows researchers to understand the relationships between variables and ensure that the data can be used for multivariate analysis. It can be difficult to evaluate missing data, outliers and the statistical characteristics of the data in a multivariate context; hence, it is important to apply data examination techniques prior to multivariate analysis. On visual examination of data, it was found that of 495 responses, 112 were from respondents not relevant to the study. Hence, these responses were excluded. This left 383 cases for further analysis. Once the data had been exported to SPSS, the data were properly labelled using several features for further analysis. Typical tasks involved in data editing are handling missing data, coding, transformation and entering data (Hair et al. 2006). These are described below.

5.3 Handling Missing and Invalid Data

Missing data are incomplete information for a case about which other information is available. It is the result of respondents' failure to answer one or more questions in a survey, leading to an incomplete survey (Hair et al. 2010). If some questions are not answered, this can create a problem for the variables created (Bryman & Bell 2011)—these data are not sufficient for exploratory factor analysis (EFA), CFA and path models, which require a specific number of data points to calculate estimates (Lynch 2006). Moreover, missing data might represent bias issues. Some respondents may not have answered particular questions in the survey because of some common issues.

According to Hair et al. (2010), missing less than 10% from a variable or respondent is not considered problematic. If the missing data are less than 10% of total responses and not categorical, it is practical to impute those responses. If the missing data are more than 10% of total responses, it may be reasonable to ignore such variables or respondents; however, this can lead to response bias and may dilute effects.

Hair et al. (2010) outlined a four-step process for identifying missing data and applying remedies. The first step is to determine the type of data missing, where the researcher assesses whether the missing data are part of the research design, the control over the data and the possibilities of ignoring certain data. If the data are operating at random, it is difficult for the researcher to predict possible values and it would be best to ignore those responses. The second step is mandatory when the missing data cannot be ignored. In this step, the researcher evaluates the extent of missing data for individual variables and overall patterns of missing data and makes a decision on deleting individual cases and/or variables. The third step is to diagnose the randomness of the missing data processes. This involves detecting whether the missing data processes are observed at random (OAR) or missing at random (MAR) or missing completely at random (MCAR) (Lynch 2007). The final step is to select an appropriate imputation method based on whether the data were observed at random or missing data are MAR or MCAR. Imputation is the process of estimating values based on other variables in the sample.

In the initial screening process, several responses were found to be 5% complete, with the extent of the missing data assessed by calculating the total number of cases with missing data. A total of 37 cases were found to be incomplete. All these cases recorded demographic data but not scores for all variables. As the data were operating at random, it was impractical to predict possible values. Moreover, the cases without variable data were not beneficial for multivariate analysis. The incomplete responses equate to 9.66% of total responses (383). In general, missing data can compromise results, but without variable data, it has no significance for multivariate analysis. Hence, these cases were excluded from further analysis. This research intended to adopt the four-step process suggested by Hair et al. (2010) to handle missing data; however, after excluding 37 cases, there were 346 cases for further examination, all of which had complete datasets.

On examining the data for missing values, further examination was conducted to check data points that fell outside the defined range for that variable of data (McBurney & White 2004). This research adopted a Likert scale rating on a 5-point scale, with 1 being strongly disagree and 5 being strongly agree. All responses were within the 1–5 range.

5.4 Examination for Outliers

Outliers are data points that are not invalid but are highly improbable. According to McBurney and White (2004), outliers can arise due to extreme scores from a normal distribution and from a different distribution than all other scores. They are not representative of the total population, but can influence results by pulling the mean away from the median. Outliers can also lead to mistaken responses. Hair et al. (2010) provide methods for detecting outliers for univariate, bivariate and multivariate analysis. Univariate outlier detection involves examining the distribution of observations for each variable and selecting cases as outliers when values are outside the normal range. Bivariate outlier detection involves assessment of pairs of variables, and multivariate outlier detection involves assessment of more than two variables. As this study utilises SEM-based multivariate analysis, the multivariate outlier detection method suggested by Hair et al. (2010) was adopted.

According to Hair et al. (2010), when more than two variables exist, the Mahalanobis D^2 measure helps to measure the multidimensional position of each observation relative to a common point. The Mahalanobis distance is a measure of the distance between a specific point and a distribution. In a normal distribution, the Mahalanobis distance is proportional to the square root of the negative log likelihood (Mahalanobis 1936). Higher D^2 values indicate outliers as they represent a distinction from other D^2 values. Hair et al. (2010) suggests 0.005 or 0.001 as conservative levels for D^2/df (df-number of variables involved); however, they suggested that $D^2/df > 2.5$ for small samples and $D^2/df > 3$ or 4 be considered possible outliers. Based on Hair et al.'s (2010) observations, 346 cases were examined to detect outliers by measuring the Mahalanobis distance (D^2) and D^2/df. Appendix D provides cases with D^2 and df values. All the cases were checked for D^2/df values, which were found to lie within the range 0–1; hence, all 346 cases were accepted for further analysis.

5.5 Multivariate Normality Tests

Normality is the shape of the data distribution for an individual metric variable and its correspondence to the normal distribution (Hair et al. 2010). Normality tests help decide whether a data set is properly modelled by a normal distribution. Researchers suggest (Ghasemi & Zahediasl 2012; Hair et al. 2010) checking data for normality as validity depends on statistical procedures and identifies any departures from normality. If the variation from the normal distribution is sufficiently large, all resulting statistical tests are invalid. According to Hair et al. (2010), severity depends on the sample size and the shape of the distribution. The sample size positively influences statistical power by reducing sampling error. When the sample size is 200 or more, significant departures from normality have little impact on the results.

Departures from normality are checked using histograms and a reliable statistical method for accuracy and validity. The shape of distribution is studied using two measures: kurtosis and skewness (Hair et al. 2010). The skewness value characterises the symmetry of the data distribution, while kurtosis refers to height, or ‘peakedness’ or ‘flatness’, of the distribution (Bryman & Bell 2011). If a frequency distribution is asymmetric with a longer tail on one end, the data are skewed: if the tail is to the low end of the distribution, it is negatively skewed; if the tail is to the higher end of the distribution, it is positively skewed (McBurney & White 2004). According to Hair et al. (2010), static values for skewness and kurtosis can be calculated as follows:

$$Z\ skewness = \frac{\text{skewness}}{\sqrt{6/N}}$$

$$Z\ kurtosis = \frac{\text{kurtosis}}{\sqrt{24/N}}$$

The critical values are from a z distribution shown in the table presented in Appendix-D. The skewness and kurtosis values are obtained to describe the data distribution. The Z-Skewness and Z-Kurtosis values ranging between −4 and +4 are considered acceptable (Tabachnick & Fidell 2019). Hair et al. (2010) suggest that skewness and kurtosis values within the ±2.58 and ±1.96 range, which correspond to 0.01 and 0.05 error levels. These values are considered acceptable. There are other lenient measures suggested by Sposito, Hand and Skarpness (1983) and Kline (2010), which consider ±2.2 and ±10 respectively as the acceptable values. However, the most commonly used critical values range is ±4 (Tabachnick & Fidell 2019). The obtained skewness and kurtosis values shown above are used to assess the degree to which the skewness and peakedness of the distribution vary from the normal distribution. The results, presented in Table 5.1, indicate that skewness and kurtosis values are within the ±4 range except skewness for STK2. Hair et al. (2010) point out that when the sample is greater than 200, then significant departures from normality have little impact on results. The sample size for this study is above 200. However, as per the more lenient measure of z-skewness and z-kurtosis (Kline 2010; Sposito, Hand & Skarpness 1983), all the z-values including STK2 are within the acceptable range. Table 5.1 presents results for the normality tests.

Table 5. 1: Normality Test Results

Variable	Skewness	Z	Kurtosis	Z	Variable	Skewness	Z	Kurtosis	Z
DOP1	-1.14	-3.13	1.45	1.99	OIP1	-0.61	-1.68	-0.17	-0.24
DOP2	-0.62	-1.69	-0.26	-0.35	OIP2	-0.64	-1.76	-0.08	-0.10
DOP3	-1.08	-2.95	0.83	1.14	OIP3	-0.72	-1.97	-0.15	-0.20
DOP4	-0.96	-2.62	0.52	0.71	OIP4	-0.89	-2.43	0.43	0.59
DOP5	-0.83	-2.28	0.26	0.36	OIP5	-0.32	-0.88	-0.69	-0.94
DOP6	-1.05	-2.86	0.83	1.14	OIP6	-0.76	-2.07	-0.03	-0.04
DOP7	-0.81	-2.22	0.26	0.35	STK1	-1.01	-2.77	0.62	0.85
INB1	-0.45	-1.23	-0.52	-0.72	STK2	-1.67	-4.57	2.41	3.30
INB2	-0.52	-1.42	-0.60	-0.82	STK3	-1.12	-3.07	1.12	1.53
INB3	-0.86	-2.36	0.10	0.14	STK4	-0.85	-2.33	0.29	0.39
OUB1	-0.48	-1.31	-0.59	-0.81	STK5	-0.51	-1.40	-0.57	-0.78
OUB2	-0.15	-0.41	-0.93	-1.27	STK6	-0.34	-0.92	-0.95	-1.29
OUB3	-0.05	-0.14	-1.10	-1.51	STK7	-0.58	-1.58	-0.60	-0.83
OUB4	-0.69	-1.89	0.07	0.10	ABS1	-1.21	-3.31	1.53	2.09
OUB5	-0.35	-0.95	-0.94	-1.28	ABS2	-0.80	-2.18	0.48	0.66
OUB6	-0.12	-0.33	-1.14	-1.56	ABS3	-0.81	-2.23	0.51	0.70
OUB7	-0.81	-2.23	0.03	0.04	ABS4	-0.79	-2.15	0.50	0.68
KSP1	-0.96	-2.62	0.94	1.29	ABS5	-0.80	-2.18	0.41	0.56
KSP2	-0.91	-2.48	0.81	1.10	INP1	-0.74	-2.01	0.44	0.61
KSP3	-0.53	-1.45	-0.30	-0.41	INP2	-0.53	-1.45	-0.25	-0.34
KSP4	-1.09	-2.97	1.16	1.59	INP3	-0.91	-2.49	0.78	1.06
KSP5	-1.23	-3.37	1.25	1.72	INP4	-0.54	-1.47	-0.52	-0.71

5.6 Non-Response Bias Estimation

Non-response bias occur particularly when there is a considerable amount of variation between those who responded and those who did not. Non-response leads to a smaller sample size relative to the proposed sample size. This can result in higher variances for the estimates and loss of accuracy. Larger samples can compensate non-response bias in certain situations where non-response has no relevance to the research variable of interest. However, if the research variable of interest is affected by non-response bias, it can distort the results (Dillman 2000).

Linsky (1975) explains that non-response bias can be brought under 30% in the majority of cases by following correct procedures. It can be addressed through sampling non-respondents. Armstrong and Overton (1977) suggest that estimation of non-response bias can be done by reanalysing early survey responses and comparing them with late responses. This will help understand the effects. Bryman and Bell (2011) indicate that most surveys end with non-responses, and it can be beneficial to keep non-response rates in mind prior to conducting surveys. They noted 20% as the possible non-response rate. This initial estimate of non-response rates significantly increases the proposed sample size. While there is no standard approach to comparing early survey results with late responses, the comparison between early responses and late responses can reveal important statistical significance.

To estimate response bias, both early responses and late responses are considered for statistical significance. This survey is on OI and innovation performance of IT organisations within and outside the IT cluster, which are influenced by organisational inbound and outbound OI. The online survey responses are labelled with survey completion dates; these dates were used to separate early responses from late responses.

As per the non-response rate estimate for surveys suggested by Bryman and Bell (2011), this research considered 20% (69 surveys) early samples and 20% (69 surveys) late samples for a two-sample t-test to study the differences (see Table 5.2).

The sigma (p-value) for the F-test indicates significant differences between the two groups for the variables OUB3, OUB5, OUB6 and STK7. The variances between the two groups are not assumed to be equal. This indicates that the two groups are not necessarily from the same population. The p-values for the t-test also suggest the variances between two groups. On further examination of the survey respondents' location (organisation location), it was found that the earlier 69 samples were completed by respondents from the organisations within the IT cluster and the later 69 samples were completed by respondents from the organisations outside the IT cluster. Earlier studies highlight an agglomeration effect on organisation’s innovation performance. This study also aims to study the moderating effect of clusters on OI in IT organisations. Considering the views of Nie and Sun (2014), Theyel (2013), Williams (2011) and Chesbrough (2006), differences between the two groups are possible. These results indicate that the statistical significance between the two groups is acceptable.

Table 5.2: Independent Sample T-test for Non-Response Bias

	Levene's Test for Equality of Variances		t-test for Equality of Means						
								95% CI of the Difference	
Variable	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
DOP1	11.457	0.001	0.491	136	0.624	0.072	0.148	-0.220	0.364
DOP2	9.382	0.003	-0.570	136	0.570	-0.116	0.203	-0.518	0.286
DOP3	15.317	0.000	0.705	136	0.482	0.145	0.206	-0.262	0.552
DOP4	14.255	0.000	-0.154	136	0.878	-0.029	0.188	-0.401	0.343
DOP5	20.092	0.000	0.386	136	0.700	0.072	0.188	-0.299	0.444
DOP6	9.553	0.002	0.512	136	0.609	0.101	0.198	-0.290	0.493
DOP7	8.140	0.005	-0.074	136	0.941	-0.014	0.196	-0.403	0.374
INB1	8.904	0.003	-1.343	136	0.181	-0.261	0.194	-0.645	0.123
INB2	9.481	0.003	-1.195	136	0.234	-0.232	0.194	-0.616	0.152
INB3	12.666	0.001	1.204	136	0.231	0.217	0.181	-0.140	0.575
OUB1	5.043	0.026	-1.095	136	0.276	-0.203	0.185	-0.569	0.164
OUB2	6.918	0.010	-2.393	136	0.018	-0.493	0.206	-0.900	-0.086
OUB3	1.395	0.240	-2.201	136	0.029	-0.493	0.224	-0.936	-0.050
OUB4	5.843	0.017	-0.548	136	0.584	-0.101	0.185	-0.467	0.265
OUB5	2.139	0.146	-1.252	136	0.213	-0.261	0.208	-0.673	0.151
OUB6	0.360	0.549	-1.701	136	0.091	-0.348	0.204	-0.752	0.057
OUB7	22.564	0.000	0.706	136	0.481	0.145	0.205	-0.261	0.551
KSP1	15.056	0.000	0.081	136	0.936	0.014	0.180	-0.341	0.370
SKP2	16.726	0.000	-0.238	136	0.812	-0.043	0.183	-0.404	0.317
KSP3	4.688	0.032	-0.790	136	0.431	-0.145	0.183	-0.508	0.218

KSP4	11.870	0.001	1.559	136	0.121	0.275	0.177	-0.074	0.625
KSP5	11.330	0.001	1.661	136	0.099	0.304	0.183	-0.058	0.667
OIP1	12.391	0.001	-0.315	136	0.753	-0.058	0.184	-0.422	0.306
OIP2	16.838	0.000	0.078	136	0.938	0.014	0.185	-0.351	0.380
OIP3	21.233	0.000	1.041	136	0.300	0.203	0.195	-0.183	0.588
OIP4	5.876	0.017	0.000	136	1.000	0.000	0.188	-0.372	0.372
OIP5	3.675	0.057	-1.131	136	0.260	-0.217	0.192	-0.598	0.163
OIP6	10.404	0.002	-0.154	136	0.878	-0.029	0.188	-0.400	0.342
STK1	5.020	0.027	0.907	136	0.366	0.159	0.176	-0.188	0.507
STK2	10.000	0.002	2.103	136	0.037	0.377	0.179	0.022	0.731
STK3	7.864	0.006	1.842	136	0.068	0.290	0.157	-0.021	0.601
STK4	18.126	0.000	0.303	136	0.762	0.058	0.191	-0.320	0.436
STK5	3.960	0.049	-0.284	136	0.777	-0.058	0.204	-0.462	0.346
STK6	8.658	0.004	-0.671	136	0.503	-0.145	0.216	-0.572	0.282
STK7	1.227	0.270	-0.770	136	0.443	-0.145	0.188	-0.517	0.227
ABS1	11.231	0.001	1.003	136	0.318	0.174	0.173	-0.169	0.517
ABS2	11.200	0.001	0.829	136	0.408	0.145	0.175	-0.201	0.490
ABS3	18.418	0.000	0.992	136	0.323	0.174	0.175	-0.173	0.521
ABS4	13.073	0.000	0.250	136	0.803	0.043	0.174	-0.301	0.388
ABS5	5.892	0.017	0.582	136	0.561	0.101	0.174	-0.243	0.446
INP1	15.744	0.000	0.519	136	0.604	0.087	0.167	-0.244	0.418
INP2	7.622	0.007	-0.342	136	0.733	-0.058	0.169	-0.393	0.277
INP3	7.615	0.007	0.238	136	0.812	0.043	0.183	-0.318	0.405
INP4	13.461	0.000	-0.722	136	0.472	-0.130	0.181	-0.488	0.227

5.7 Tests for Common Method Bias

Common method bias or common method variance is the measurement error that is the result of the instrument itself rather than the actual responses that the instrument aims to uncover. Biased instruments can lead to distorted and inaccurate results (Podsakoff, MacKenzie & Podsakoff 2012a); therefore, it is important to check whether the data suffer from common method bias.

Several researchers have stressed the potential problems associated with common method bias. To understand the extent of the common method bias problem, Harman's single factor score is commonly used. This test is considered reliable and helps to understand if a single factor can explain the total variance. In this approach, all measurement items are loaded into one common factor to compute total variance for that single factor. In other words, all the observed variables are specified into the model, then the number of factors constrained to be one. This is done using an unrotated solution to understand the total variance by a single factor. Table 5.3, 5.4 and 5.5 present the results for common method bias test.

Table 5.3: Test for Common Method Bias-Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	24.401	55.456	55.456	24.401	55.456	55.456
2	2.733	6.211	61.667	2.733	6.211	61.667
3	1.443	3.280	64.947	1.443	3.280	64.947
4	1.073	2.439	67.387	1.073	2.439	67.387
5	0.919	2.089	69.476	0.919	2.089	69.476
6	0.802	1.822	71.298	0.802	1.822	71.298
7	0.741	1.684	72.982	0.741	1.684	72.982
8	0.690	1.569	74.551	0.690	1.569	74.551
9	0.635	1.443	75.994	0.635	1.443	75.994
10	0.606	1.378	77.372	0.606	1.378	77.372
11	0.574	1.305	78.678	0.574	1.305	78.678
12	0.564	1.281	79.959	0.564	1.281	79.959
13	0.486	1.104	81.063	0.486	1.104	81.063
14	0.476	1.081	82.144	0.476	1.081	82.144
15	0.461	1.048	83.193	0.461	1.048	83.193
16	0.437	0.993	84.185	0.437	0.993	84.185

17	0.420	0.954	85.139	0.420	0.954	85.139
18	0.388	0.882	86.021	0.388	0.882	86.021
19	0.374	0.851	86.872	0.374	0.851	86.872
20	0.365	0.830	87.702	0.365	0.830	87.702
21	0.347	0.789	88.491	0.347	0.789	88.491
22	0.336	0.764	89.254	0.336	0.764	89.254
23	0.304	0.691	89.945	0.304	0.691	89.945
24	0.303	0.688	90.633	0.303	0.688	90.633
25	0.298	0.678	91.311	0.298	0.678	91.311
26	0.279	0.634	91.945	0.279	0.634	91.945
27	0.268	0.610	92.555	0.268	0.610	92.555
28	0.265	0.603	93.158	0.265	0.603	93.158
29	0.261	0.593	93.751	0.261	0.593	93.751
30	0.251	0.569	94.320	0.251	0.569	94.320
31	0.245	0.556	94.877	0.245	0.556	94.877
32	0.230	0.522	95.399	0.230	0.522	95.399
33	0.229	0.521	95.920	0.229	0.521	95.920
34	0.211	0.480	96.400	0.211	0.480	96.400
35	0.208	0.472	96.872	0.208	0.472	96.872
36	0.202	0.458	97.330	0.202	0.458	97.330
37	0.182	0.414	97.744	0.182	0.414	97.744
38	0.169	0.384	98.127	0.169	0.384	98.127
39	0.151	0.343	98.470	0.151	0.343	98.470
40	0.149	0.338	98.808	0.149	0.338	98.808
41	0.145	0.331	99.138	0.145	0.331	99.138
42	0.136	0.310	99.449	0.136	0.310	99.449
43	0.128	0.292	99.740	0.128	0.292	99.740
44	0.114	0.260	100.000	0.114	0.260	100.000

According to Podsakoff, MacKenzie and Podsakoff (2012b), a total variance score less than 50% suggests that the data are not affected by common method bias. However, results suggest that the total variance is 55.456%. As these data consist of samples collected from inside and outside a cluster, further tests are conducted to gain an in-depth understanding of the reasons for exceeding total variance.

Table 5.4: Test for Common Method Bias – Total Variance Explained (Cluster)

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	20.624	46.873	46.873	20.624	46.873	46.873
2	3.224	7.328	54.201	3.224	7.328	54.201
3	1.908	4.336	58.537	1.908	4.336	58.537
4	1.320	2.999	61.537	1.320	2.999	61.537
5	1.100	2.500	64.037	1.100	2.500	64.037
6	1.042	2.368	66.404	1.042	2.368	66.404
7	0.949	2.156	68.560	0.949	2.156	68.560
8	0.865	1.965	70.525	0.865	1.965	70.525
9	0.794	1.804	72.329	0.794	1.804	72.329
10	0.768	1.744	74.074	0.768	1.744	74.074
11	0.744	1.691	75.764	0.744	1.691	75.764
12	0.710	1.613	77.377	0.710	1.613	77.377
13	0.651	1.480	78.857	0.651	1.480	78.857
14	0.593	1.348	80.204	0.593	1.348	80.204
15	0.575	1.306	81.511	0.575	1.306	81.511
16	0.546	1.240	82.751	0.546	1.240	82.751
17	0.518	1.176	83.927	0.518	1.176	83.927
18	0.467	1.061	84.988	0.467	1.061	84.988
19	0.456	1.037	86.024	0.456	1.037	86.024
20	0.428	0.973	86.997	0.428	0.973	86.997
21	0.415	0.943	87.941	0.415	0.943	87.941
22	0.388	0.881	88.822	0.388	0.881	88.822
23	0.368	0.835	89.657	0.368	0.835	89.657
24	0.345	0.783	90.441	0.345	0.783	90.441
25	0.330	0.750	91.191	0.330	0.750	91.191
26	0.308	0.699	91.890	0.308	0.699	91.890
27	0.296	0.672	92.563	0.296	0.672	92.563
28	0.285	0.647	93.209	0.285	0.647	93.209
29	0.269	0.612	93.822	0.269	0.612	93.822
30	0.256	0.582	94.404	0.256	0.582	94.404
31	0.250	0.568	94.971	0.250	0.568	94.971
32	0.245	0.556	95.527	0.245	0.556	95.527
33	0.224	0.509	96.036	0.224	0.509	96.036
34	0.214	0.486	96.522	0.214	0.486	96.522
35	0.201	0.458	96.980	0.201	0.458	96.980

36	0.193	0.438	97.418	0.193	0.438	97.418
37	0.182	0.413	97.831	0.182	0.413	97.831
38	0.168	0.383	98.214	0.168	0.383	98.214
39	0.162	0.368	98.581	0.162	0.368	98.581
40	0.155	0.352	98.933	0.155	0.352	98.933
41	0.134	0.306	99.239	0.134	0.306	99.239
42	0.121	0.275	99.513	0.121	0.275	99.513
43	0.112	0.254	99.768	0.112	0.254	99.768
44	0.102	0.232	100.000	0.102	0.232	100.000

Table 5.5: Test for Common Method Bias – Total Variance Explained (Outside Cluster)

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	28.800	65.455	65.455	28.800	65.455	65.455
2	1.698	3.858	69.313	1.698	3.858	69.313
3	1.204	2.737	72.050	1.204	2.737	72.050
4	1.037	2.357	74.407	1.037	2.357	74.407
5	0.904	2.054	76.461	0.904	2.054	76.461
6	0.754	1.714	78.175	0.754	1.714	78.175
7	0.711	1.616	79.791	0.711	1.616	79.791
8	0.676	1.536	81.327	0.676	1.536	81.327
9	0.649	1.474	82.801	0.649	1.474	82.801
10	0.554	1.259	84.060	0.554	1.259	84.060
11	0.531	1.208	85.268	0.531	1.208	85.268
12	0.466	1.060	86.328	0.466	1.060	86.328
13	0.453	1.029	87.357	0.453	1.029	87.357
14	0.439	0.999	88.356	0.439	0.999	88.356
15	0.383	0.871	89.227	0.383	0.871	89.227
16	0.376	0.854	90.081	0.376	0.854	90.081
17	0.368	0.836	90.917	0.368	0.836	90.917
18	0.326	0.741	91.657	0.326	0.741	91.657
19	0.296	0.673	92.330	0.296	0.673	92.330
20	0.284	0.645	92.976	0.284	0.645	92.976
21	0.262	0.595	93.571	0.262	0.595	93.571
22	0.257	0.584	94.155	0.257	0.584	94.155
23	0.256	0.581	94.736	0.256	0.581	94.736
24	0.209	0.475	95.211	0.209	0.475	95.211

25	0.186	0.423	95.634	0.186	0.423	95.634
26	0.172	0.391	96.025	0.172	0.391	96.025
27	0.170	0.386	96.411	0.170	0.386	96.411
28	0.157	0.358	96.769	0.157	0.358	96.769
29	0.152	0.346	97.115	0.152	0.346	97.115
30	0.143	0.325	97.440	0.143	0.325	97.440
31	0.138	0.313	97.753	0.138	0.313	97.753
32	0.128	0.290	98.043	0.128	0.290	98.043
33	0.113	0.256	98.299	0.113	0.256	98.299
34	0.109	0.247	98.546	0.109	0.247	98.546
35	0.096	0.218	98.764	0.096	0.218	98.764
36	0.089	0.201	98.965	0.089	0.201	98.965
37	0.082	0.187	99.152	0.082	0.187	99.152
38	0.075	0.171	99.323	0.075	0.171	99.323
39	0.066	0.149	99.472	0.066	0.149	99.472
40	0.062	0.140	99.612	0.062	0.140	99.612
41	0.054	0.124	99.736	0.054	0.124	99.736
42	0.044	0.100	99.836	0.044	0.100	99.836
43	0.042	0.096	99.932	0.042	0.096	99.932
44	0.030	0.068	100.000	0.030	0.068	100.000

Harman's one-factor analysis conducted on the data collected from the cluster indicated a total variance of 46.873%; however, Harman's one-factor test on data collected from outside the cluster suggested a 65.455% total variance.

The counterarguments to Harman's single-factor test for common method bias suggest that measuring total variance by a single factor is not psychometrically convincing. Scholars further argue that Harman's single-factor score is not a rule of thumb, but helps if the total variance can be explained with one factor (Podsakoff, MacKenzie & Podsakoff 2012). In this case, survey samples are from two independent groups, which can be a reason for high variance. Hence, a total variance of 55.45% was accepted.

5.8 Respondent Profile

This section details the profile of the respondents, their area of employment, main products and services of their organisations, number of employees working and the profile of their customers. Table 5.6 outlines the sample composition. Survey respondents are from business process, consulting, corporate function/leadership, education and training, marketing/sales, R&D and technology areas. However, the majority, about 59.53%, participate in developing new application software and providing technical support to clients. Results reveal that the main products and services of the participants' organisations include BPO and software development (55.78%), education, training and certification (8.67%), IT marketing and sales (15.02%), IT support and maintenance (12.13%), telecommunications and networking (3.46%), R&D (2.31%) and others (2.60%). The sample consists of 17.34% small organisations with up to 50 employees, 20.23% medium-sized organisations with up to 200 employees and 62.42% large organisations with more than 200 employees. 4.62% of survey respondents suggested that their organisation provides services to overseas customers only and 27.45% indicated that they have domestic customers only. However, 67.91% indicated that they provide services to both domestic and overseas customers.

Table 5.6: Respondent Profile

Characteristics	N (%)	Characteristics	N (%)
Main products and services		Respondents field	
BPO and Software Development	193 (55.78%)	Business process	4 (1.15%)
Education, Training & Certification	30 (8.67%)	Consulting	25 (7.22%)
IT marketing & sales	52 (15.02%)	Corporate function/Leadership	55 (15.89%)
IT support & maintenance	42 (12.13%)	Education and Training	20 (5.78%)
Telecommunications & Networking	12 (3.46%)	Marketing/Sales	21 (6.06%)
Research & Development	8 (2.31%)	Research & Development	11 (3.17%)
Others	9 (2.60%)	Technology	206 (59.53%)
		Others	4 (1.15%)
No. of employees in the organisation		Customer type	
Small businesses 0-50	60 (17.34%)	Domestic only	95 (27.45%)
Medium businesses 51–200	70 (20.23%)	Overseas only	16 (4.62%)
Large businesses Above 200	216 (62.42%)	Both domestic and overseas	235 (67.91%)

5.9 Summary

This chapter detailed the procedures associated with data preparation and analysis. This research utilised the RMIT University-approved online data collection tool Qualtrics to collect data. On collecting the samples, the data were checked for missing and invalid data. As per the suggestion of Hair et al. (2010), the data were also checked for outliers.

Multivariate normality tests were conducted to check whether the data set was properly modelled by a normal distribution. Non-response bias was estimated by testing both early responses and late responses for statistical significance. To test common method bias, Harman's single-factor score was used.

Chapter 6: Instrument Validation and Measurement Model

6.1 Introduction

The objective of this chapter is to outline the steps followed to evaluate the validity and reliability of the measurement instrument used for this study (see Figure 6.1). This chapter is organised into seven sections. Section 6.2 provides a summary of steps adopted to maintain content validity. Section 6.3 details steps involved in purifying the initial measure. Section 6.4 focusses on establishing dimensionality via Exploratory Factor Analysis (EFA). Section 6.5 explains the process used for construct validity with convergent validity and discriminant validity. Section 6.6 details the final reliability test. Section 6.7 provides a summary of the contents presented in this chapter.

Scholars have reiterated the importance of instrument validation for positivist and quantitative studies (Straub, Boudreau & Gefen 2004). A reliable and valid measure helps to represent underlying phenomena and achieve objectivity for data collection. Moreover, an absence of bias implies that the findings of the analysis might be reliable. The terms reliability and validity seem like synonyms, however, they have different meanings in relation to the assessment of measures of concepts (Bryman & Bell 2011). Reliability concerns the issues associated with the consistency of measures. It assesses stability, internal reliability and inter-observer consistency. The stability aspect considers whether or not a measure is stable over time; a measure is considered stable if there are few variations in results when the measure is readministered. Internal reliability involves assessing whether index indicators are consistent, and inter-observer consistency arises in situations where the researcher needs to make judgements about how to classify respondents' behaviour obtained in the form of responses for open-ended questions (Bryman & Bell 2011). Validity can be defined as the extent to which a data collection instrument measures what it is intended to measure; in other words, it is the degree of arrangement between the real environment and the adopted measurement. There are multiple ways to assess validity, including 'face validity, concurrent validity, predictive validity, construct validity and convergent validity' (Bryman & Bell 2011, p. 159).

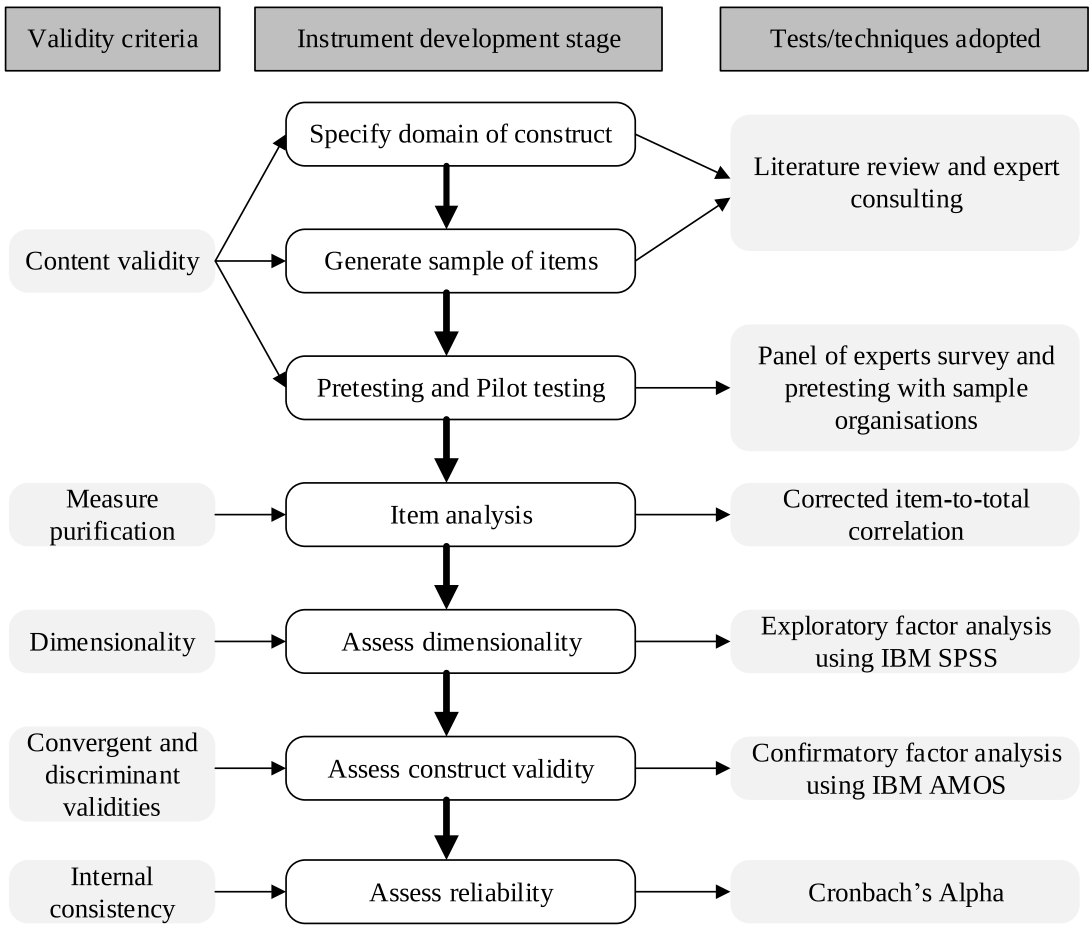

Figure 6.1: Instrument Development and Validation Processes

6.2 Content Validity

Content validity is used to assess the construct using the body of knowledge surveyed. It is the evaluation of the relevance of the variables included in a measurement scale based on conceptual characterisation (Hair et al. 2010). In other words, it is 'the degree to which elements of an assessment instrument are relevant to and representative of the targeted construct for a particular assessment purpose' (Haynes, Richard & Kubany 1995). In psychometric tests, this is considered the extent to which the variables are relevant and represent a given construct. It is also called logical validity and seen as a prerequisite, as it helps understand whether the desired phenomenon is measured. It assumes that constructs are comprised of the concept and the variable, which is the measurement target (Haynes, Richard & Kubany 1995).

Content validity emphasises variables of the construct and their representation in the measurement model. Hair et al. (2010) suggest that this form of validity is also known as face validity. However, it can be argued that face validity is different from content validity, as face validity aims to examine whether the test looks valid to observers who are not experts (Gravetter & Forzano 2012; Holden 2010), while the content validity test measures what it is supposed to measure and the relevance of the variable to a specified construct. Failure to ensure content validity can lead to potential bias, as test elements may measure something that is unrelated to the main construct.

Literature (Ebel 1961; MacKenzie, Podsakoff & Podsakoff 2011) presents a four-step process for establishing content validity (see Figure 6.2). The initial step is to outline and define the construct to be measured. The next step is to define the content domain to represent the construct with identifiable dimensions. The third step is to establish a plan to test the basis of domain knowledge used to define the construct. The final step is to involve a panel of subject matter experts examining the questionnaire items to decide on whether the knowledge measured by each item is essential and the extent to which chosen items sufficiently sample from the subject domain.

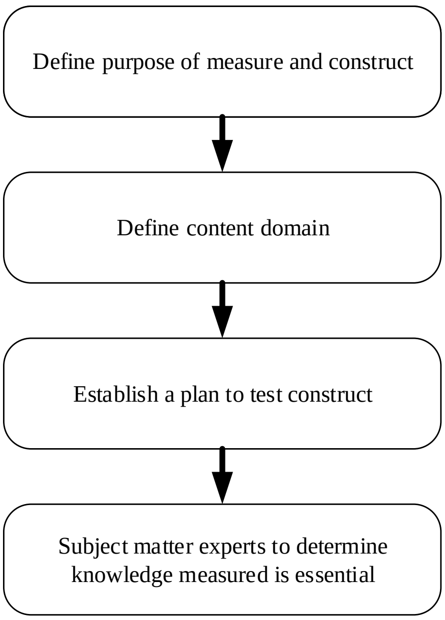

Figure 6.2: Steps in Establishing Content Validity

This study used literature reviews and subject matter experts to establish content validity. Straub, Boudreau and Gefen (2004) suggest pre-testing and pilot testing as alternatives that help identify sources of error and refine the instrument. Pre-testing involves testing some of the instrument aspects, whereas the pilot test involves testing a small sample of the population to be used for the final survey. This study used the following steps to establish content validity:

- Chapter 2 presented underlying theories behind OI and innovation performance. An exhaustive literature review was conducted to define the domain constructs presented in Chapter 3. This provided an in-depth understanding of the concept and the relevance of items. The relevant items were presented in Chapter 4.
- The pre-testing method suggested by Straub, Boudreau and Gefen (2004) was used to evaluate the suitability of items for the constructs to be measured. The evaluation was done by subject matter experts to improve content validity and reliability.
- A pilot test was conducted with five organisations of the sample frame to which the final survey questionnaire would be distributed. This helped to identify flaws that might have been present in the instrument.

6.3 Measure Purification

Measurement is the allocation of scores to observations to quantify observation for easier analysis (Kimberlin & Winterstein 2008). According to Churchill (1979), a measurement instrument may include some items that are not completely relevant to the other items in that instrument. Kimberlin and Winterstein (2008) explain that some of the measures from the data sources can be objective, as these have little error margins and meet various standards. The classical test theory suggests that results obtained by a measurement instrument consist of both true and error scores. The true score indicates accuracy, because it is the score that would have been received if the survey items were accurate. However, the data sources involving a higher degree of subjectivity are the usual sources of error in measurement. These error sources can distort results. Churchill (1979) suggests that these error sources need to be identified and excluded to achieve reliability.

Reliability can be defined as the internal consistency of a measurement instrument. Initial reliability tests are used to assess the stability of the measures tested at various times with the same respondents using the same standard. Reliability coefficients can be anywhere between 0.00 and 1.00. Higher coefficients indicate higher levels of reliability. Cronbach's α is the most commonly used test for assessing internal consistency, with values above 0.80 generally considered acceptable (Nunnally & Bernstein 1994). Another test using the composite reliability measure (ρ) considers values above 0.50 to be reliable (Jöreskog & Sörbom 1984).

Bryman and Bell (2011) suggest that the most commonly used method for measuring internal consistency is Cronbach's α, as it calculates the average of all possible reliability coefficients. An alpha coefficient 0 indicates no internal reliability and 1 indicates perfect internal reliability. Values above 0.70 should be considered a rule of thumb sufficient for internal consistency (Bryman & Bell 2011; Hair et al. 2010). Hair et al. (2010) suggest item-to-total correlation for the measure purification and to assess how each item of a construct relates to other items. They explain that lower item-to-total values indicate that an item may not be relevant to the construct and warrants deletion to avoid potential measurement errors. Field (2009) provides 0.3 as the minimum value to be considered acceptable item-to-total value (Churchill 1979), and suggests that measurement items with values lesser than 0.3 be dropped to avoid measurement errors.

Based on the suggestions of Bryman and Bell (2011) and Hair et al. (2010), this study checked alpha coefficients to purify the measure. Cronbach's α values above 0.8 and item-to-total values above 0.3 indicate high levels of reliability. Table 6.1 shows Cronbach's α values and item-to-total (item-to-total correlation) values and the possible Cronbach's α values if a particular item is deleted. The initial reliability test suggests that the Cronbach's α values of 0.84 and above are reliable and sufficient for achieving internal consistency.

Table 6.1: Cronbach's α and Item-to-Total (Item-to-Total Correlation) Values

Construct	Cronbach's α	Item	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Squared multiple correlation	Cronbach's α if item deleted
Degree of openness	0.91	DOP1	23.27	25.406	0.721	0.531	0.898
		DOP2	23.79	23.682	0.718	0.538	0.898
		DOP3	23.53	23.676	0.769	0.608	0.892
		DOP4	23.53	23.844	0.737	0.569	0.895
		DOP5	23.62	24.108	0.734	0.552	0.896
		DOP6	23.54	23.815	0.736	0.556	0.896
		DOP7	23.74	24.122	0.694	0.493	0.900
Inbound innovation	0.84	INB1	7.62	3.604	0.765	0.609	0.722
		INB2	7.57	3.486	0.756	0.603	0.732
		INB3	7.10	4.592	0.616	0.380	0.863
Outbound innovation	0.91	OUB1	20.60	34.304	0.734	0.576	0.903
		OUB2	20.97	33.002	0.769	0.645	0.899
		OUB3	21.15	31.627	0.783	0.674	0.898
		OUB4	20.49	35.509	0.682	0.527	0.908
		OUB5	20.86	32.041	0.793	0.648	0.897
		OUB6	20.99	32.165	0.762	0.654	0.900
		OUB7	20.41	35.187	0.667	0.487	0.910
Knowledge spill-overs	0.87	TSP1	15.82	10.171	0.760	0.578	0.841
		TSP2	15.85	10.254	0.713	0.517	0.852
		TSP3	16.07	10.219	0.664	0.475	0.864
		TSP4	15.73	10.146	0.731	0.562	0.847
		TSP5	15.64	10.323	0.686	0.509	0.858
Innovation practices	0.91	OIP1	18.79	19.273	0.808	0.662	0.892
		OIP2	18.81	19.241	0.799	0.655	0.893
		OIP3	18.79	19.103	0.766	0.599	0.897
		OIP4	18.77	19.684	0.721	0.525	0.904
		OIP5	18.97	19.437	0.730	0.541	0.902
		OIP6	18.80	19.431	0.728	0.541	0.903
Stakeholder engagement (direct)	0.87	STK1	23.45	25.663	0.701	0.573	0.888
		STK2	23.18	26.540	0.650	0.601	0.894
		STK3	23.39	25.925	0.736	0.592	0.886
		STK4	23.88	23.842	0.761	0.673	0.881
Stakeholder engagement	0.90	STK5	24.09	23.146	0.750	0.707	0.883
		STK6	23.88	24.061	0.721	0.603	0.886

(indirect)		STK7	23.66	25.334	0.679	0.508	0.891
Absorptive capacity	0.92	ABS1	15.76	11.008	0.757	0.579	0.913
		ABS2	15.90	10.868	0.796	0.637	0.906
		ABS3	15.94	10.652	0.804	0.661	0.904
		ABS4	15.92	10.750	0.825	0.692	0.900
		ABS5	15.92	10.551	0.812	0.668	0.902
Innovation performance	0.90	INP1	11.53	7.415	0.766	0.597	0.888
		INP2	11.57	7.248	0.799	0.647	0.876
		INP3	11.44	7.117	0.803	0.649	0.874
		INP4	11.71	6.666	0.796	0.645	0.879

6.4 Assessment of Dimensionality Using Exploratory Factor Analysis

Scholars (Lewis, Byrd & Templeton 2005; Straub, Boudreau & Gefen 2004) have provided guidelines to assess dimensionality (factorial validity) with the help of Exploratory Factor Analysis (EFA). According to Furr (2011), it is important to consider various dimensionality issues to understand the dimensions reflected in the items, which helps in determining relevance, assessment and interpretation. EFA is the most common approach used for assessing the dimensionality of psychological scales as it reveals whether a scale’s items are unidimensional or multidimensional (Thompson 2004). In case of unidimensionality, all items reflect one common variable; multidimensional items may reflect more than one variable and dimensionality may be correlated with one another due to relevance in variables.

EFA is said to be exploratory and require a no priori hypothesis about factors, for example, which items to load to which factor (Finch & West 1997), because it assumes that measured variables may be associated with any factor (Furr 2011). However, it can be used on restricted models to determine latent factors (Kline 2010). As EFA inspects constructs without need of theoretical connections, scholars suggest using EFA prior to CFA.

The appropriateness of the data for the nine EFA models was confirmed by checking the factorability of the data and the sample size. The Kaiser-Meyer-Olkin (KMO) test is the most common method used to measure sampling adequacy (i.e., the suitability of data for factor analysis). It is the proportion of variance among variables, which suggests the sampling adequacy for each variable in the proposed model and for the entire model. KMO values range from 0 to 1, and higher values indicate the sample is adequate. Bartlett's test of sphericity (BTOS) helps to determine whether variances are the same across groups or samples. Values less than 0.05 are generally considered not suitable for factor analysis. Hair et al. (2010) suggest that KMO values should lie between 0.5 and 1, and BTOS values less than 0.05. The KMOSA and BTOS values presented in Table 6.2 suggest that the data are suitable for nine EFA models. The subject-to-variable ratio is considered important as it can determine the accuracy of EFA (MacCallum & Tucker 1991). A minimum subject-to-variable ratio of 10:1 is suggested by Garson (2012); however, Bryant and Yarnold (1995) used a more conservative approach, a subject-to-variable ratio of 5:1. Hair et al. (2010) suggest a 5:1 to 10:1 range as a minimum. As per Hair et al. (2010, p. 102), the minimum sample size should be at least five times the number of variables to be analysed, which is equivalent to 220. There are 44 variables and the sample size is 346, which is equivalent to a 7.8:1 ratio. The selected sample size satisfies the subject-to-variable ratio, indicating appropriateness for EFA.

Table 6.2: KMOSA and BTOS for the Constructs

Construct	No. of items	KMOMSA	BTOS	Observation
Degree of openness	7	0.924	0.000	EFA supported
Inbound innovation	3	0.695	0.000	EFA supported
Outbound innovation	7	0.894	0.000	EFA supported
Technological spill-overs	5	0.862	0.000	EFA supported
Open innovation practices	6	0.918	0.000	EFA supported
Stakeholder engagement (direct)	4	0.824	0.000	EFA supported
Stakeholder engagement (indirect)	3	0.736	0.000	EFA supported
Absorptive capacity	5	0.896	0.000	EFA supported
Innovation performance	4	0.841	0.000	EFA supported
Overall	44	0.863	0.000	EFA supported

EFA is centred on the common factor model and assumes that each variable may be associated with any factor (Norris & Lecavalier 2009). As there is no one particular method, on confirming the appropriateness of the data for factor analysis, the following tasks were conducted to extract factors.

To estimate the regression coefficients between items and factors (factor loadings) and unique variances and error variance, the most common extraction method in information systems research, Principal Component Analysis (PCA), was used (Hair et al. 2010). PCA produces predictive models and explains relatedness between populations using an eigenvalue decomposition of a data correlation.

Factors are extracted using eigenvalues (latent root criterion). Hair et al. (2010) suggest Kaiser's (1960) eigenvalue-greater-than-one rule, where an eigenvalue > 1 is used to extract factors. Kaiser's criterion is suitable where there are fewer than 40 variables, and it produces the most accurate factor structure with a lesser number of variables. The current study consists of 44 variables; thus, pre-setting an eigenvalue to > 1 could lead to under factoring. Jolliffe's criterion suggests retaining factors with an eigenvalue of 0.70 or above (Jolliffee1972, 1973, 2002), and this was selected here.

The factors were rotated using varimax rotation, an orthogonal rotation method that minimises the number of high loading variables on every factor and load items to factors visibly (Young & Pearce 2013). Scholars (Field 2009; Hair et al. 2010) suggest that the minimum correlation 'r' should be 0.50 to allocate items to a factor. However, the correlation 'r' should be set depending on the sample size, as a smaller sample size requires a higher loading and a smaller loading for a sample size more than 200. The suggested sample loading is 0.30 (Tabachnick & Fidell 2019) or 0.40 (Hair et al. 2010). The sample size for this study is 346, hence the 'r' value has been set to 0.40. Items with factor loadings below 0.40 were dropped from further analysis.

The other approaches for the number of factors to extract include priori criterion, percentage of variance criterion, Scree test criterion and heterogeneity of the respondents. These approaches have significant drawbacks compared with the latent root criterion (Hair et al. 2010). However, Yong and Pearce (2013) point out that if there is theoretical reasoning, it is acceptable to extract a specific number of factors by specifying the fixed number of factors to be extracted. EFA was conducted for all items in accordance with the literature.

In summary, the following rules were implemented for the EFA:

- PCA
- Varimax rotation (orthogonal rotation method)
- Eigenvalue threshold for factor extraction > 0.7
- Item values (factor loadings) less than 0.4 were dropped.

The results of the three EFA models are presented below in Tables 6.3, 6.4, 6.5, 6.6, 6.7 and 6.8. The technical input dimension produced a three-factor structure (see Table 6.3), which explains 56.5% of variance. The KMO test produces an acceptable value of 0.94 and BTOS presents a significance value of 0.000. The factor loadings are above 0.70 for all items and no issues were reported.

Table 6.3: Initial Results of Exploratory Factor Analysis – I

Construct	Item	Factors			Comments
		1	2	3	
Degree of openness	DOP1	0.76	0.51		Suppressed small coefficients (values below 0.40) DOP1 - Cross-loading. The difference between loadings is greater than 0.20. Hence, no further action is needed
	DOP2	0.76			
	DOP3	0.82			
	DOP4	0.78			
	DOP5	0.77			
	DOP6	0.78			
	DOP7	0.73			
Stakeholder engagement (direct)	STK1		0.80		
	STK2		0.84		
	STK3		0.80		
	STK4		0.72		
Stakeholder engagement (indirect)	STK5			0.85	
	STK6			0.92	
	STK7			0.80	

The business model dimension produced a two-factor structure (see Table 6.4), which explains 61.4% of variance. The KMO test produces an acceptable value of 0.94 and BTOS presents a significance value of 0.000. The factor loadings are above 0.70 for all the items except for the item KSP3; item KSP3, with significant cross-loading on innovation practices, was dropped. The other items, OIP1 and OIP2 with cross-loading on knowledge spill-overs, were retained as the respective cross-loadings were less than 0.50 and the difference between loadings was greater than 0.20 (Costello, Jason & Osborne 2005).

Table 6.4: Initial Results of Exploratory Factor Analysis – II

Construct	Item	Factors 1	2	Comments
Innovation practices	OIP1	0.75	0.43	OIP1 and OIP2 cross-loadings but the difference between loadings is greater than 0.20
	OIP2	0.75	0.42	
	OIP3	0.82		
	OIP4	0.70		
	OIP5	0.80		KSP3 – Cross-loading. The difference between loadings is less than 0.20. Hence, KSP3 is deleted
	OIP6	0.70		
Knowledge spill-over	KSP1		0.76	
	KSP2		0.75	
	KSP3	0.52	0.56	
	KSP4		0.79	
	KSP5		0.78	

The open innovation and economic output dimensions produced a three-factor structure (see Table 6.5), which explains 59.8% of variance. The KMO test produces an acceptable value of 0.94 and BTOS presents a significance value of 0.000. The items OUB4 and OUB7 from the construct outbound innovation cross-loaded with innovation performance with respective values 0.59 and 0.63. As a result, these two items were dropped from further analysis.

Table 6.5: Initial Results of Exploratory Factor Analysis – III

Construct	Item	Factors 1	2	3	Comments
Inbound innovation	INB1	0.76			
	INB2	0.73			
	INB3	0.68			
Outbound innovation	OUB1		0.65		OUB4 and OUB7 cross-loaded with INNP. Hence OUB4 and OUB7 are deleted
	OUB2		0.82		
	OUB3		0.82		
	OUB4		0.48	0.59	
	OUB5		0.76		
	OUB6		0.74		
	OUB7		0.49	0.63	
Innovation performance	INP1			0.79	
	INP2			0.77	
	INP3			0.82	
	INP4			0.64	

The AC dimension produced a one-factor structure (see Table 6.6), which explains 76.4% of variance. The KMO test produces an acceptable value of 0.90 and BTOS presents a significance value of 0.000. The factor loadings for all items are greater than 0.85 and cross-loadings are not reported.

Table 6.6: Results of Exploratory Factor Analysis – IV

Construct	Item	Component
Absorptive capacity	ABS1	0.85
	ABS2	0.87
	ABS3	0.88
	ABS4	0.90
	ABS5	0.89

Table 6.7 presents the final EFA output and Table 6.8 a summary of the final EFA output. A total of three items, one from knowledge spill-overs and two from outbound innovation constructs, were dropped during EFA due to cross-loadings. The results prove factorial validity and signify an initial specification of the measurement model.

Table 6.7: Final Results of Exploratory Factor Analysis

Domain	Construct	Item	1	2	3	4	5	6	7	8	9
Technical inputs	Degree of openness	DOP1	0.76								
		DOP2	0.76								
		DOP3	0.82								
		DOP4	0.78								
		DOP5	0.77								
		DOP6	0.78								
		DOP7	0.73								
	Stakeholder engagement (direct)	STK1		0.80							
		STK2		0.84							
		STK3		0.80							
		STK4		0.72							
	Stakeholder engagement (indirect)	STK5			0.85						
		STK6			0.92						
		STK7			0.80						
Business models	Innovation practices	OIP1				0.75					
		OIP2				0.75					
		OIP3				0.82					
		OIP4				0.70					
		OIP5				0.80					
		OIP6				0.70					
	Knowledge spill-overs	KSP1					0.76				
		KSP2					0.75				
		KSP4					0.79				
		KSP5					0.78				
Open innovation	Inbound innovation	INB1						0.76			
		INB2						0.73			
		INB3						0.68			
	Outbound innovation	OUB1							0.65		
		OUB2							0.82		
		OUB3							0.82		
		OUB5							0.76		
		OUB6							0.74		
Economic outputs	Innovation performance	INP1								0.79	
		INP2								0.77	
		INP3								0.82	

		INP4	0.64	
Absorptive capacity	Absorptive capacity	ABS1		0.85
		ABS2		0.87
		ABS3		0.88
		ABS4		0.90
		ABS5		0.89

Table 6.8: Summary of the EFA Output

Domain	Construct	No. of items before EFA	Dropped items	Comments	Factor labels	No. of items after EFA
Technical inputs	Degree of openness	7	None	DOP1 cross-loaded with direct stakeholder engagement	Degree of openness	7
	Stakeholder engagement (direct)	4	None	None	Direct stakeholders	4
	Stakeholder engagement (indirect)	3	None	None	Indirect stakeholders	3
Business models	Innovation practices	6	None	None	Innovation practices	6
	Knowledge spill-overs	5	1	KSP3 cross-loaded with innovation practices	Knowledge spill-overs	4
Open innovation	Inbound innovation	3	None	None	Inbound innovation	3
	Outbound innovation	7	2	OUB4 and OUB7 cross-loaded with innovation performance	Outbound innovation	5
Economic outputs	Innovation performance	4	None	None	Innovation performance	4
Absorptive capacity	Absorptive capacity	5	None	None	Absorptive capacity	5

The next section conducts further tests of these initial results for construct validity through CFA.

6.5 Assessment of Construct Validity Through CFA

Confirmatory Factor Analysis (CFA) is a statistical technique that verifies how well measured variables represent a small number of constructs. It allows researchers to study the relationship between observed variables and the factor structure of grouped and observed variables (Hair et al. 2010).

Both EFA and CFA are powerful statistical methods. EFA assesses the relation between all measured variables and every factor using a factor loading estimate to estimate the number of factors needed to represent the data. EFA can be done without preconceived knowledge on theory in relation to how many factors exist and the relevance of measured variables to constructs. In case of CFA, the researcher needs to specify both the number of factors and associated variables for each factor (Hair et al. 2010). It allows the researcher to test hypotheses developed on the basis of empirical research (Schumacker & Lomax 1996). In other words, it is a confirmatory test for the proposed measurement theory (Hair et al. 2010).

Hair et al. (2010) suggest that in exploring the possibilities to decide the number of factors through EFA and testing the research hypotheses developed through empirical research, construct validity needs to be assessed using CFA. Schumacker and Lomax (1996) explain that the use of CFA is affected by the sample size, outliers, missing data, hypotheses being tested and interpretation of model fit indices. Scholars (Hair et al. 2010; Lohelin 1998) argue that the researcher needs to consider a sample size of more than 200 to reveal the associations between the observed variables and the underlying constructs. The sample size for this study is 346, which meets the minimum sample size requirement for CFA.

After identifying the number of factors, CFA was conducted via SEM to evaluate construct validity with the help of model fit indices. SEM measures causal relationships between latent variables and predict variable outcomes (Child 1990). Hence, it is a measurement model (Byrne 2001). CFA is a special case of SEM. According to Hair et al. (2010), SEM is a widely accepted method for assessing construct validity and theoretical relationships among constructs. It is a hybrid factor analysis method that combines both multiple regression and factor analysis (Everitt & Hothorn 2006). There are several software applications such as LISREL, AMOS and EQS to conduct SEM. This study uses IBM AMOS, commonly used in information systems research.

6.5.1 Goodness of Fit

The goodness of fit (GOF) model explains divergence between observed values and those expected in a proposed model. It helps the researcher to compare results with theory. Each GOF measure is unique, and these measures are grouped into absolute measures, incremental measures and parsimony fit measures (Hair et al. 2010). This study includes chi-square in addition to the above three measures (see Table 6.9).

Table 6.9: Category of GOF Indices (Hair et al. 2010)

Category	Statistics	Definition
Chi-square	Chi-square	Assessment of differences between groups using nominal data
	Degrees of freedom	Estimated parameters subtracted from total coefficients
	Probability statistic (p)	Probability of closeness between the observed and covariance matrices
Absolute fit indices	GOF index	Indicator for model reproducibility to demonstrate variance or covariance of the observed sample
	RMSEA	Measure of fit/misfit in SEM applications to explain how well a model fits a population
	RMR	The mean absolute value of the covariance residuals
	SRMR	Standardised root mean square residual compares fit across models
	Normed chi-square	Ratio of X^2 to the degrees of freedom for a model
Incremental fit indices	Normed fit index (NFI)	Ratio of the difference in X^2 (fitted model) divided by X^2 (null model)
	Tucker-Lewis index (TLI)	Comparison of normed chi-square (null model) against chi-square of specified model
	Comparative fit Index (CFI)	Incremental fit index
	Incremental fit indices (IFI)	Comparison of null model against specified model
Parsimony fit indices	Parsimony comparative fit index (PCFI)	Result from CFI CFI multiplied by the PR
	Parsimony normed fit index (PNFI)	Result from NFI NFI multiplied by the PR
PClose	Close-fitting model	P-value of a test on RMSEA

Sivo et al. (2006) identified 13 fit indexes and determined cut-off values. Similarly, Hooper, Coughlan and Mullen (2008) used the chi-squared test, root mean square error of approximation (RMSEA), GFI, AGFI, the root mean square residual (RMR) and the standardised root mean residual (SRMR) to demonstrate that the proposed model fits the data. As there are various GOF measures, scholars (Hair et al. 2010; Kline 2010) suggest using at least three fit indices. A study into the search for optimal cut-off values indicates that the ideal values may change according to sample size; for example, lower cut-off values are observed with a smaller sample size. Hence, at least 200 samples are recommended (Hair et al. 2010; Kline 2010). The sample size for this study is 346. Table 6.10 provides a summary of selected fit measures with acceptable value ranges.

Table 6.10: Summary of Chosen GOF Measures and Criteria

Measure type	Selected GOF statistics	Traditional acceptable value range	Source
Chi-square	Chi-square X^2 (df, p*)	$P < 0.05$	Barrett, 2007; Hair et al. 2010;
Absolute fit indices	Relative/Normed chi-square (X^2/df)	<5 ($\leq$3 preferred)	Tabachnick & Fidell, 2019; Hoe, 2008; Hair et al. 2010
	RMSEA	< 0.5–0.10	Hoe, 2008; Hu & Bentler, 1999; Hair et al. 2010
	RMR and SRMR	< 0.09	Byrne, 1998; Hu & Bentler, 1999; Hair et al. 2010
Incremental fit indices	CFI, TLI and IFI	> 0.90	Hooper, Coughlan & Mullen 2008
Parsimony fit indices	PNFI and PCFI	> 0.5	Hooper, Coughlan & Mullen 2008; Hair et al. 2010
PClose	PClose	>0.05	Hox & Bechger 1991

6.5.2 Convergent Validity

Convergent validity is a subcategory of construct validity. It is a parameter to evaluate the extent to which two measures of construct converge, which should be related in accordance with the theory, are related in reality. It can be established by demonstrating correspondence between two similar constructs. Hair et al. (2010) suggest indicators including factor loadings size, average variance extracted (AVE) and reliability to establish convergent validity. In the AMOS software, convergent validity can be established using one or more GOF measures, including squared multiple correlation (SMC), standardised factor loading (SFL), AVE and construct reliability (CR).

According to Hair et al. (2010), evidence of convergent validity exists if the SFL are greater than 0.7, AVE is greater than 0.5, CR is greater than 0.7 and SMC are greater than 0.4.

6.5.3 Discriminant Validity

Discriminant validity is a subtype of construct validity. Both convergent validity and discriminant validity provide evidence of relationship or no relationship between constructs. Both tests are conducted to demonstrate correspondence or lack thereof between two similar constructs (Hair et al. 2010; Hooper, Coughlan & Mullen 2008). Discriminant validity is used to demonstrate that constructs that should not be related are in reality not related. It demonstrates the uniqueness of each construct by capturing the phenomena the other construct does not have. It can be established by specifying the correlation between the two constructs as equal to one and comparing the two-construct model against a one-construct model. The variance can be used to support discriminant validity (Hair et al. 2010; Hooper, Coughlan & Mullen 2008).

Segars (1997) suggested the chi-square difference test to assess discriminant validity. In this approach, two models are compared, 'one in which the constructs are correlated and one in which they are not' (Zait & Bertea 2011). To assess discriminant validity, the constructs to be analysed are taken in pairs and the CFA without correlating these constructs is performed. Then, the constructs are correlated and the CFA is performed. Evidence of discriminant validity exists if the chi-square difference test is significant (Zait & Bertea 2011). The other approach is to compare the AVE values of any two constructs against the correlation estimation square between these constructs. If the obtained variance value is greater than the squared correlation estimate, discriminant validity is established (Hair et al. 2010). Although there are various tests to assess discriminant validity, the chi-square difference test is more accurate as it shows even small differences between the constructs (Segars 1997; Zait & Bertea 2011). Hence, this study used the chi-square difference test to assess discriminant validity.

6.5.4 Measurement Model for Technical Inputs Constructs

Earlier sections detailed first-order measurement models. In the second-order models, first-order constructs are considered variables. The specification of the second-order model is similar to the first-order model. Hair et al. (2010) explains that second-order factor models can be decided based on reasoning including (1) a theoretical justification for more than one conceptual layer, (2) influence of first-order factors on other related constructs, (3) prediction of other constructs using higher-order factors and (4) presence of good measurement practice in both layers.

Higher-order models may be useful in some circumstances because of sufficient fit, predictability of conceptually related constructs and better predictive validity. As it uses fewer degrees of freedom, its performance on parsimony indices is important (Hair et al. 2010).

Congeneric Measurement Model for Degree of Openness Construct

The degree of openness construct was hypothesised to consist of seven items. The proposed one-factor congeneric measurement model based on CFA is presented in Figure 6.1. The SFLs are displayed above the arrows from the latent variable (degree of openness) towards the seven individual items. The SMC values for each item are presented just above the arrow reaching point.

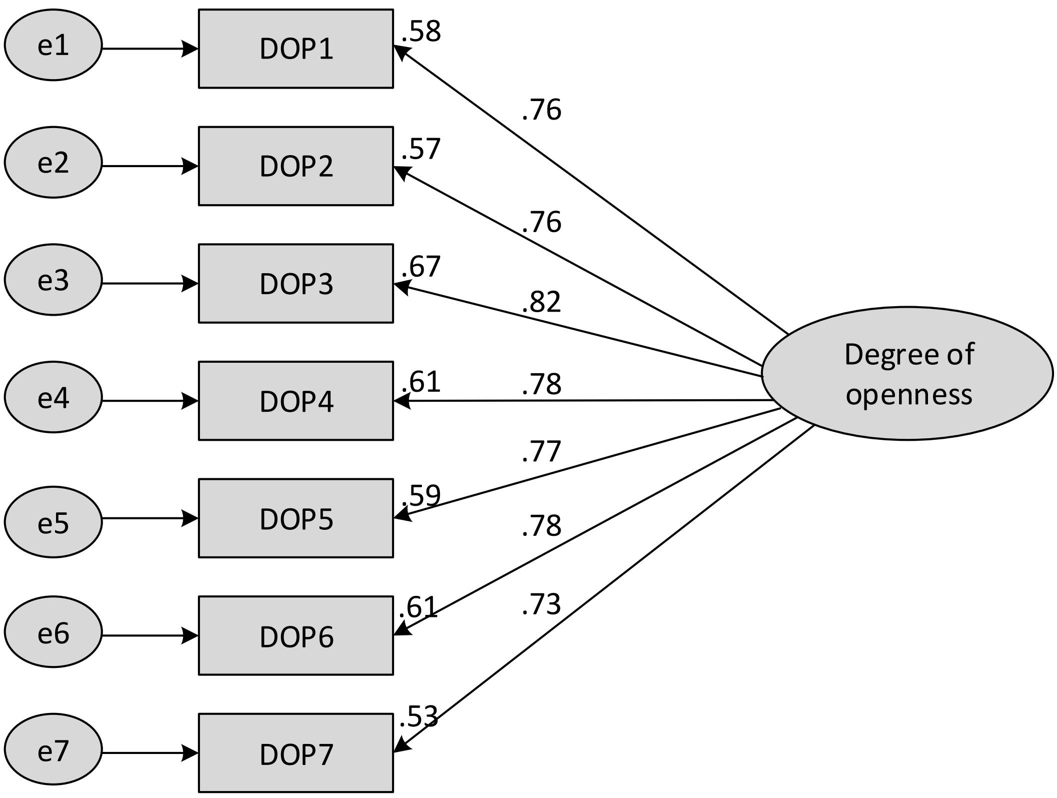

Figure 6.3: One-factor Congeneric Model for Degree of Openness

To assess GOF, the following indices were evaluated:

- absolute fit indices, including the normed chi-square (X^2/df) (Wheaton et al. 1977 in Hooper, Coughlan & Mullen 2008, p. 54; Hair et al. 2010, p. 649), RMSEA (Hair et al. 2010; Hoe 2008; Hu & Bentler 1999), RMR and standardised value of RMR (SRMR) (Byrne 1998; Hair et al. 2010)

- incremental fit indices, including comparative fit index (CFI), Tucker-Lewis index (TLI) and incremental fit index (IFI) (Hooper, Coughlan & Mullen 2008; Hu & Bentler 1999)

- parsimony fit indices, including the parsimony normed fit index (PNFI) and parsimony comparative fit index (PCFI) (Hair et al. 2010; Hooper et al. 2008) and P-value (Hair et al. 2010; Barrett 2007).

Table 6.11: Statistics for the Proposed One-factor Congeneric Measurement Model of Degree of Openness

Chi-square		Absolute fit indices		Incremental fit indices		Parsimony fit indices	
X^2	113.742(0.00)	RMSEA	0.05	CFI	0.97	PCFI	0.65
DF	42	RMR	0.03	IFI	0.97	PNFI	0.64
X^2/df	2.708	SRMR	0.05	TLI	0.96	Pclose	0.5

Factor loadings
($P < 0.001$***, $P < 0.01$**, $P < 0.05$*)

Item	SE	CR	P	SMC	Comment
DOP1	0.76	11.372	***	0.583	Convergent validity holds
DOP2	0.76	10.529	***	0.573	
DOP3	0.82	11.073	***	0.667	
DOP4	0.78	11.199	***	0.611	
DOP5	0.77	11.141	***	0.595	
DOP6	0.78	11.675	***	0.605	
DOP7	0.73	11.334	***	0.527	
Model fit is excellent					

The proposed model for the degree of openness has 42 degrees of freedom. The model fit statistics indicate that the values are within the acceptable range. The chi-square (X^2/df) value of 2.708 is within the acceptable range. The absolute fit indices (RMSEA, RMR and SRMR), incremental fit indices (CFI, IFI and TLI) and parsimony fit indices

(PCFI and PNFI) values are within the range. The SFL are greater than 0.7 and SMC are greater than 0.4 (Hair et al. 2010). These values establish construct validity and suggest that the proposed model is admissible. Table 6.11 presents statistics for the proposed one-factor congeneric measurement model of degree of openness.

Congeneric Measurement Model for Direct Stakeholder Engagement Construct

The stakeholder engagement construct was hypothesised to consist of seven items. The proposed one-factor congeneric measurement model based on CFA is presented in Figure 6.4. The SFLs are displayed above the arrows from the latent variable (stakeholder engagement) towards the seven individual items. The SMC values for each item are presented just above the arrow reaching point.

The proposed one-factor model for direct stakeholder engagement is identified with a chi-square value of 11.895 and six degrees of freedom. The normed chi-square value is 1.983, which is well below the threshold. The absolute fit index, root mean square residual and standardised RMR values are within the acceptable range. The incremental fit index (CFI, IFI and TLI) values are above 0.90. The RMSEA value of 0.04 suggests good model fit. The standardised estimates for STK1, STK2, STK3 and STK4 are above 0.7 and the SMC values are above 0.5. Table 6.12 presents statistics for the proposed one-factor model for stakeholder engagement. Evidence of construct validity exists if the SFL and SMC values are above 0.7 and 0.3 (preferably 0.5). The proposed model is a good fit and there is no need to respecify the model.

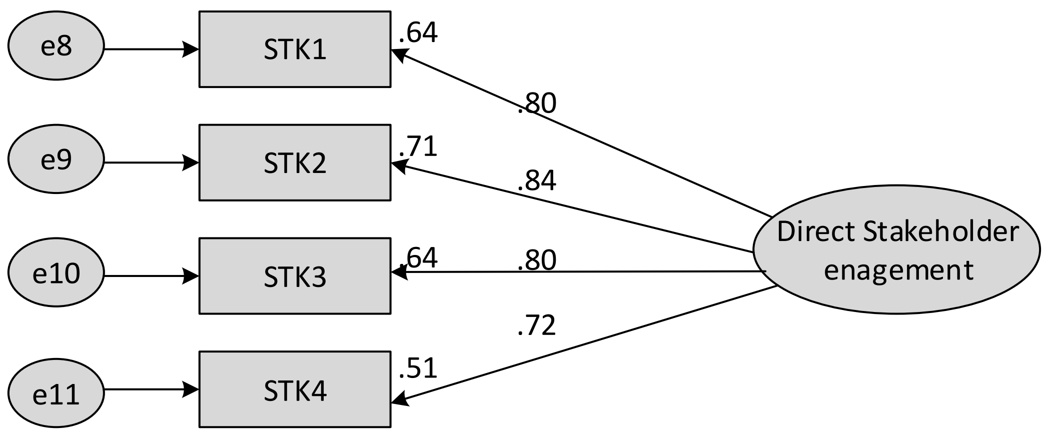

Figure 6.4: Proposed One-factor, Congeneric Model for Direct Stakeholder Engagement

Table 6.12: Statistics for Proposed One-factor, Congeneric Measurement Model of Direct Stakeholder Engagement

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	11.895(0.05)	RMSEA	0.04	CFI	0.99	PCFI	0.34
DF	6	RMR	0.01	IFI	0.99	PNFI	0.34
X^2/df	1.983	SRMR	0.02	TLI	0.99	Pclose	0.07

Factor loadings
($P < 0.001$***, $P < 0.01$**, $P < 0.05$*)

Item	SFL	CR	P	SMC	Comment
STK1	0.80	8.116	***	0.64	Convergent validity holds
STK2	0.84	9.603	***	0.71	
STK3	0.80	11.082	***	0.64	
STK4	0.72	9.539	***	0.51	

Model fit is admissible

Proposed One-factor Congeneric Measurement Model for Indirect Stakeholder Engagement Construct

The indirect stakeholder engagement construct was hypothesised to consist of three items. The CFA results of the proposed one-factor congeneric measurement model are presented in Figure 6.5.

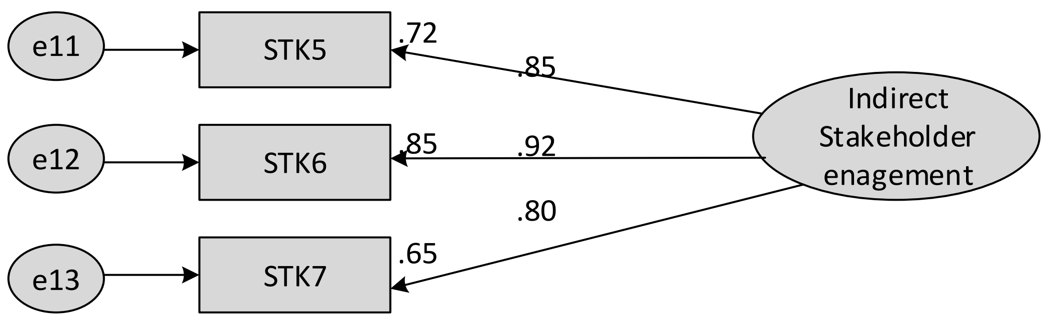

Figure 6.5: Proposed One-factor Congeneric Model for Indirect Stakeholder Engagement

The proposed model for indirect stakeholder engagement is identified with chi-square value of 8.100 and six degrees of freedom. The normed chi-square value is 1.35, which is below the threshold of 3. The absolute fit index RMSEA value of 0.02 is within the range. The incremental fit index (CFI, IFI and TLI) values are above 0.90. The RMSEA value of 0.02 suggests a good model fit. The standardised estimates for STK4, STK5 and STK6 are above 0.8. These values establish construct validity and convergent validity (Hair et al. 2010). Table 6.13 presents statistics for the proposed one-factor model for indirect stakeholder engagement. Evidence of construct validity exists if the SFL and SMC values are above 0.7 and 0.3 (preferably 0.5). The proposed model is a good fit and there is no need to respecify the model. For the other absolute fit indices, root mean square residual and standardised RMR values, the SRMR value of 0.002 is within the acceptable range, however, the RMR value is well above the range. Hooper, Coughlan and Mullen (2008) explain that the RMR value is dependent on the scales of each indicator and a low value indicates a good fit. They suggest using SRMR values when it is difficult to achieve low RMR values. The SRMR value of 0.002 is closer to 0, indicating a perfect fit. The other fit indices including incremental fit indices, parsimony fit indices and the normed chi-square values are within the acceptable range. Hence, this model has been accepted.

Table 6.13: Statistics for Proposed One-Factor, Congeneric Measurement Model of Indirect Stakeholder Engagement

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	8.100(.23)	RMSEA	0.02	CFI	0.99	PCFI	0.67
DF	6	RMR	0.19	IFI	0.99	PNFI	0.67
X^2/df	1.35	SRMR	0.002	TLI	0.99	Pclose	0.89

Factor loadings
($P < 0.001$***, $P < 0.01$**, $P < 0.05$*)

Item	SFL	CR	P	SMC	Comment
STK5	0.85	9.052	***	0.72	Convergent validity holds
STK6	0.92	5.390	***	0.85	
STK7	0.80	10.542	***	0.65	
Model fit is admissible					

Full Measurement Model for Technical Inputs

This section presents the validity of the three constructs forming the technical inputs domain. The congeneric measurement models for technical inputs constructs degree of openness, direct stakeholder engagement and indirect stakeholder engagement are presented. All three constructs were individually examined and validated.

Figure 6.6 presented below shows the full measurement model for the technical inputs domain. Table 6.14 presents results associated with construct validity and GOF statistics.

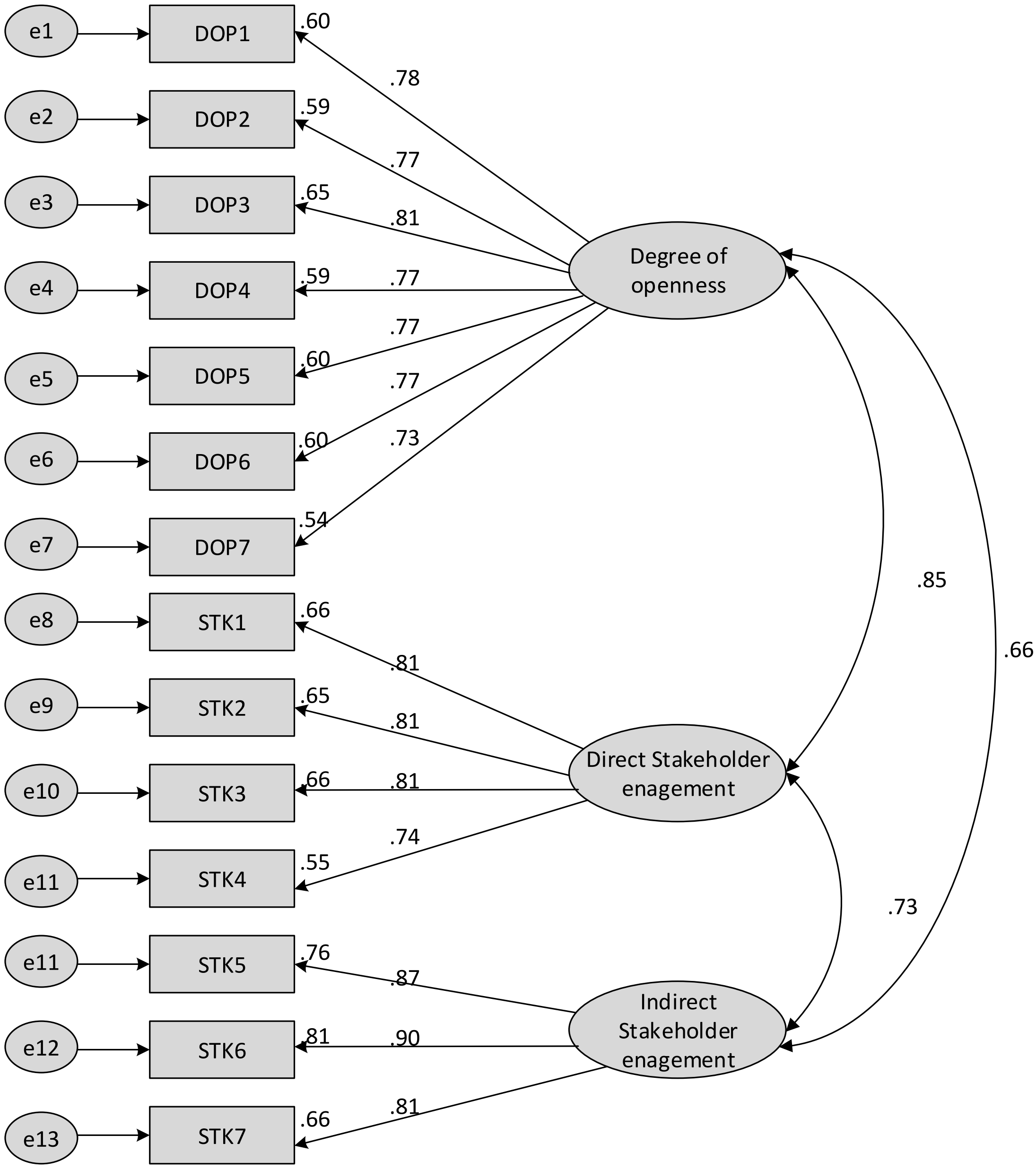

Figure 6.6: Full First-Order Measurement Model for Technical Inputs Constructs

The results presented in Table 6.15 suggest an acceptable fit. The normed chi-square value is below 3. The other fit indices (absolute, incremental and parsimony) were examined and values were found to be within the acceptable range. The Pclose value of

0.34 also suggests a good model fit. The SFL are greater than 0.7, the SMC are greater than 0.4 and the CR values are greater than 0.7 (Hair et al. 2010). The SFL, SMC and CR values provide evidence of convergent validity. Table 6.14 presents GOF statistics that suggest that the proposed full model for technical inputs domain is admissible.

Table 6.14: Goodness of Fit Statistics and Validity Measures for Technical Inputs

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	622.025(0.00)	RMSEA	0.05	CFI	0.94	PCFI	0.76
DF	222	RMR	0.06	IFI	0.94	PNFI	0.74
X^2/df	2.802	SRMR	0.05	TLI	0.92	Pclose	0.34

Factor loadings
(P < 0.001***, P < 0.01**, P < 0.05*)

Factor	CR	AVE	Item	SFL	SMC	Comment
DOP	0.91		DOP1	0.78	0.60	
			DOP2	0.77	0.59	
			DOP3	0.81	0.65	
			DOP4	0.77	0.59	
			DOP5	077	0.60	
			DOP6	0.77	0.60	
		0.60	DOP7	0.73	0.54	
Direct STK	0.87		STK1	0.81	0.66	
			STK2	0.81	0.65	
			STK3	0.81	0.66	
		0.63	STK4	0.74	0.55	
Indirect STK	0.90		STK5	0.87	0.76	
			STK6	0.90	0.81	
		0.74	STK7	0.81	0.66	

Evidence of convergent validity and discriminant validity

On examining the model fit statistics and establishing convergent validity, further tests were conducted to establish discriminant validity. The chi-square difference tests are conducted for the constructs presented in the full model (see figure 6.6). The constructs to be analysed are taken in pairs and CFA was performed with and without correlating the constructs. The results presented in Table 6.15 indicate that the chi-square difference tests are significant, suggesting discriminant validity.

Table 6.15: Discriminant Validity of Constructs in the Technical Inputs Domain

Construct		CR	AVE	Degree of Openness			Direct stakeholders			Indirect stakeholders		
				X^2	Df	P	X^2	Df	P	X^2	Df	P
DOP	Correlation set free	0.902	0.605				856.593	132	*	582.6	105	*
	Correlation						328.502	129	*	270.671	102	*
	Difference						528.091	3	*	311.929	3	*
Direct STK	Correlation set free	0.896	0.743	856.593	132	*				510.492	42	*
	Correlation			328.502	129	*				142.300	39	*
	Difference			528.091	3	*				368.192	3	*
Indirect STK	Correlation set free	0.871	0.628	582.6	105	*	510.492	42	*			
	Correlation			270.671	102	*	142.300	39	*			
	Difference			311.929	3	*	368.192	3	*			

Significance: P < 0.001*, P < 0.01**, P < 0.05***

6.5.5 Measurement Model for Business Models Constructs

Congeneric One-factor Measurement Model for Innovation Practices Construct

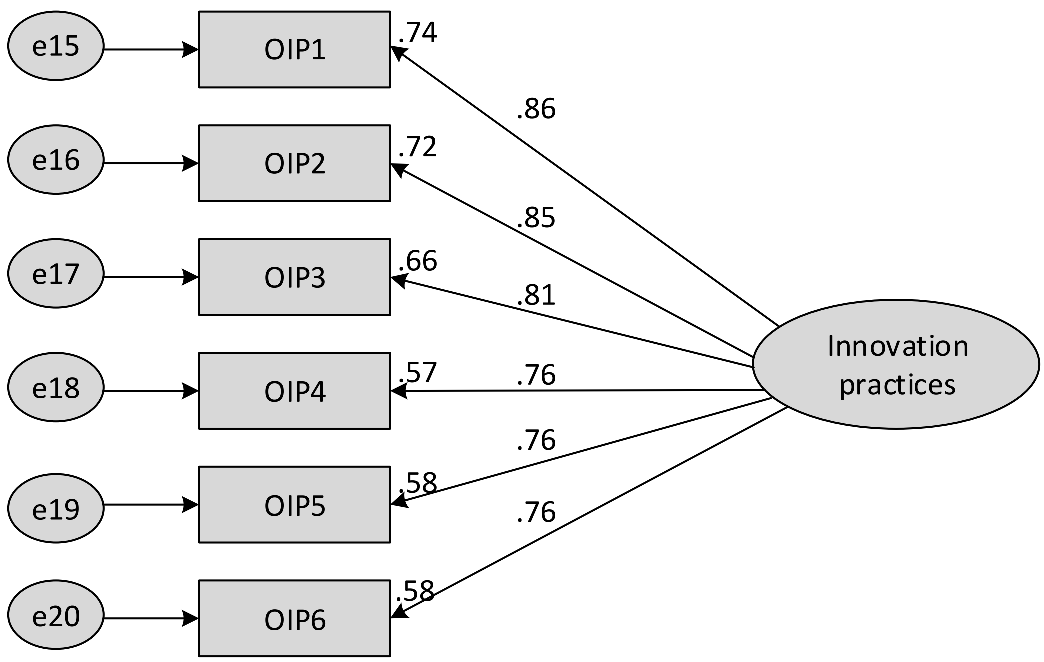

Figure 6.7: Proposed One-factor, Congeneric Model for Innovation Practices

The innovation practices construct was theorised as consisting of six items: organisational efforts to inform employees about the significance of OI, encouraging them through rewards and seeking feedback to improve access to external knowledge.

These items are examined for whether they represent the sample data. The CFA results of the proposed one-factor congeneric measurement model are presented in Figure 6.7.

The proposed model for innovation practices is identified with a chi-square value of 42.240 and 27 degrees of freedom. The normed chi-square value is 1.564, which is below the threshold of 3. The RMR and SRMR values are 0.03 and 0.02 respectively. The RMSEA value of 0.03 suggests a good model fit. The incremental fit index (CFI, IFI and TLI) values are above 0.99. The standardised estimates for OIP1, OIP2, OIP3, OIP4, OIP5 and OIP6 are above 0.7.

Table 6.16 presents statistics for the proposed one-factor model for innovation practices. Evidence of construct validity exists if the SFL and SMC values are above 0.7 and 0.3 (preferably 0.5). These values establish construct validity and convergent validity (Hair et al. 2010). The other fit indices including parsimony fit indices and normed chi-square values are within the acceptable range. The proposed model is a good fit and there is no need to respecify the model. Hence, this model has been accepted.

Table 6.16: Statistics for Proposed One-factor, Congeneric Measurement Model of Innovation Practices

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	42.240(0.03)	RMSEA	0.03	CFI	0.99	PCFI	0.60
DF	27	RMR	0.03	IFI	0.99	PNFI	0.60
X^2/df	1.564	SRMR	0.02	TLI	0.99	Pclose	0.99

Factor loadings
(P < 0.001***, P < 0.01**, P < 0.05*)

Item	SE	CR	P	SMC	Comment
OIP1	0.86	9.832	***	0.74	Model is identified
OIP2	0.85	10.035	***	0.72	
OIP3	0.81	10.866	***	0.66	
OIP4	0.76	11.544	***	0.57	
OIP5	0.76	11.473	***	0.58	
OIP6	0.76	11.481	***	0.58	

Model fit is excellent

Congeneric One-factor Measurement Model for Knowledge Spill-overs Construct

The knowledge spill-overs construct was hypothesised to consist of five items. However, the item KSP3 (Our organisation acquires knowledge/technology developed by institutions such as Universities, Professional bodies, R&D laboratories, etc.) was deleted during EFA because of cross-loadings with innovation practices. The CFA results of the proposed one-factor congeneric measurement model are presented in Figure 6.8.

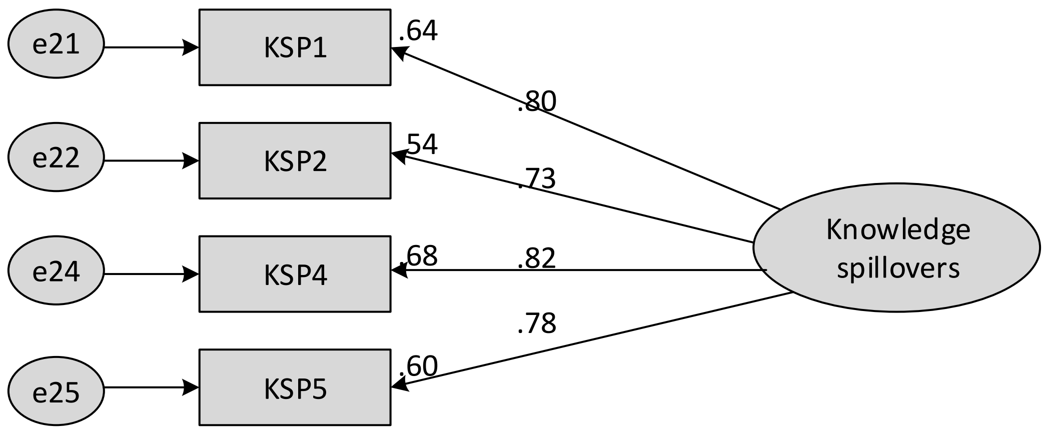

Figure 6.8: Proposed One-factor, Congeneric model for Knowledge Spill-overs

The proposed model for indirect stakeholder engagement is identified with a chi-square value of 16.198 and 6 degrees of freedom. The normed chi-square value is 2.70, which is below the threshold of 3. The absolute fit indices (RMSEA, RMR and SRMR) and their respective values 0.05, 0.02 and 0.02 are within the acceptable range. The incremental fit index (CFI, IFI and TLI) values are above 0.97. The parsimony fit index (PCFI and PNFI) values and Pclose value are within the range.

Table 6.17 presents statistics for the proposed one-factor model for knowledge spill-overs. The standardised estimates for KSP1, KSP2, KSP4 and KSP5 are above 0.7 and the SMC values are above 0.5. Evidence of construct validity exists if the SFL and SMC values are above 0.7 and 0.3 (preferably 0.5). The values presented in Table 6.17 establish construct validity and convergent validity (Hair et al. 2010). The proposed model is a good fit and there is no need to respecify the model. Hence, this model is accepted.

Table 6.17: Statistics for Proposed One-factor, Congeneric Measurement Model of Knowledge Spill-overs

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	16.198(0.01)	RMSEA	0.05	CFI	0.99	PCFI	0.33
DF	6	RMR	0.02	IFI	0.99	PNFI	0.33
X^2/df	2.70	SRMR	0.02	TLI	0.97	Pclose	0.46

Factor loadings
($P < 0.001$***, $P < 0.01$**, $P < 0.05$*)

Item	SE	CR	P	SMC	Comment
KSP1	0.80	9.175	***	0.64	Model is identified
KSP2	0.73	10.641	***	0.54	
KSP3	Item deleted due to cross-loadings				
KSP4	0.82	8.564	***	0.68	
KSP5	0.78	9.965	***	0.60	
Model fit is acceptable					

Full Measurement Model for Second-order Constructs

This section presents the validity of the two constructs forming the business model domain. The congeneric measurement models for business models constructs innovation practices and knowledge spill-overs are presented earlier. Both the constructs in this domain were individually examined and validated.

Figure 6.9 shows the full measurement model for the business model domain. Table 6.18 presents results associated with construct validity and GOF statistics.

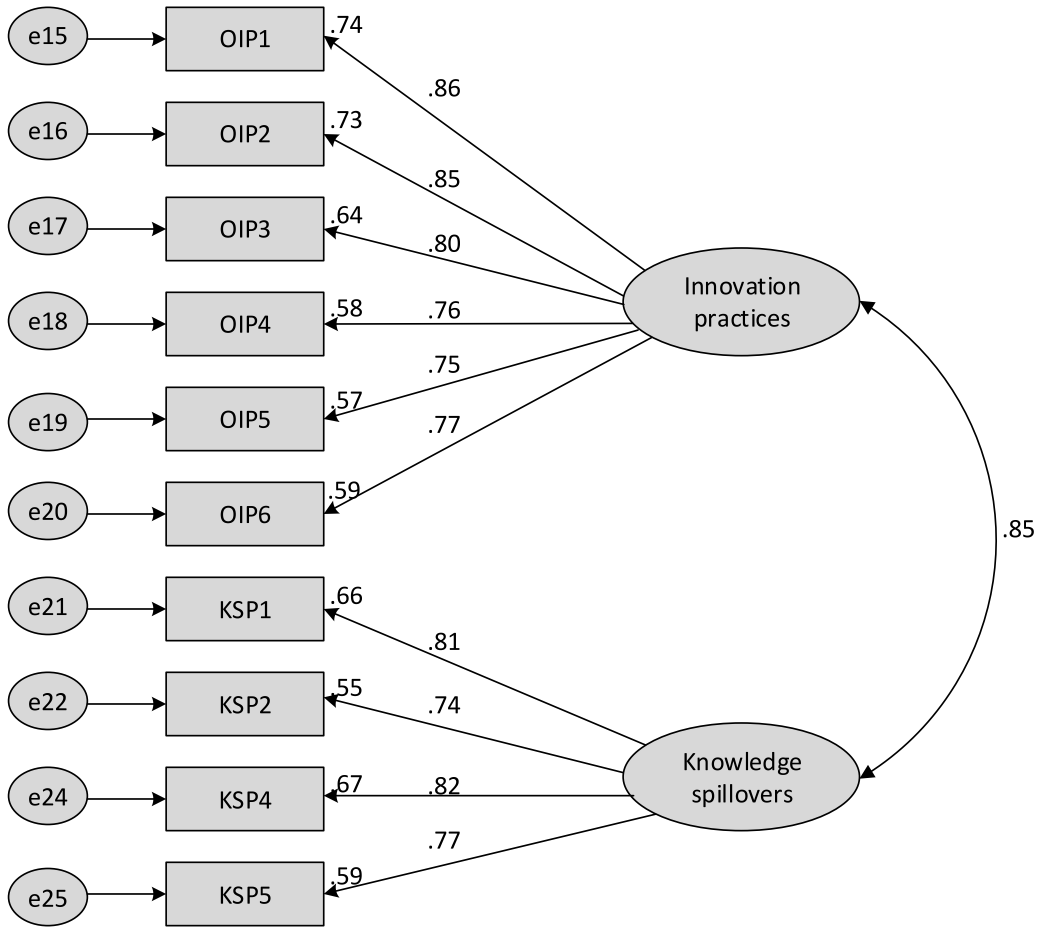

Figure 6.9: Full First-order Measurement Model for Business Models Constructs

The results presented in Table 6.18 suggest an acceptable fit. The normed chi-square value is 2.15. The absolute (RMSEA, RMR and SRMR), incremental (CFI, IFI and TLI) and parsimony (PCFI and PNFI) fit indices were examined and the values were found to be within the acceptable range. The Pclose value of 0.98 also suggests a good model fit. The SFL are greater than 0.7, the SMC are greater than 0.4 and the CR values are greater than 0.7 (Hair et al. 2010). The SFL, SMC and CR values provide evidence of convergent validity. The GOF values presented in Table 6.18 suggest that the proposed full model is admissible.

Table 6.18: Goodness of Fit Statistics and Validity Measures for Business Models Constructs

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	219.290(0.00)	RMSEA	0.04	CFI	0.97	PCFI	0.74
DF	102	RMR	0.04	IFI	0.97	PNFI	0.72
X^2/df	2.15	SRMR	0.03	TLI	0.97	Pclose	0.98

Factor loadings

Factor	CR	AVE	Item	SFL	SMC	Comment
OIP	0.91	0.64	OIP1	0.86	0.74	
			OIP2	0.85	0.73	
			OIP3	0.80	0.64	
			OIP4	0.76	0.58	
			OIP5	0.75	0.57	
			OIP6	0.77	0.59	
KSP	0.85	0.64	KSP1	0.81	0.66	
			KSP2	0.74	0.55	
			KSP3	Deleted		
			KSP4	0.82	0.67	
			KSP5	0.77	0.59	

Model fit is acceptable

On examining the model fit statistics and establishing convergent validity, further tests were conducted to establish discriminant validity. The chi-square difference tests were conducted for the constructs presented in the full model (Figure 6.9). The constructs in this domain are taken in pairs and CFA performed with and without correlating the constructs innovation practices and knowledge spill-overs. The results, presented in Table 6.19, indicate that the chi-square difference tests are significant, suggesting discriminant validity.

Table 6.19: Discriminant Validity of Business Models Constructs

Construct	Correlation	CR	AVE	Innovation practices			Knowledge spill-overs		
				Chi-square	df	P	Chi-square	df	P
Innovation practices	Correlation set free						813.893	105	*
	Correlation						219.29	102	*
	Difference	0.91	0.64				594.603	3	*
Knowledge spill-overs	Correlation set free			813.893	105	*			
	Correlation			219.29	102	*			
	Difference	0.85	0.64	594.603	3	*			

Significance: P < 0.001*, P < 0.01**, P < 0.05***

6.5.6 Full Measurement Model for Technical Input and Business Model Constructs

This section presents the validity of the two constructs forming the business model domain. Sections 6.5.4 and 6.5.5 presented the congeneric measurement models for technical inputs and business models constructs. All the constructs in these two domains were individually examined and validated.

Figure 6.10 shows the full measurement model for the technical inputs and business models domains. Table 6.20 presents results associated with construct validity and GOF statistics.

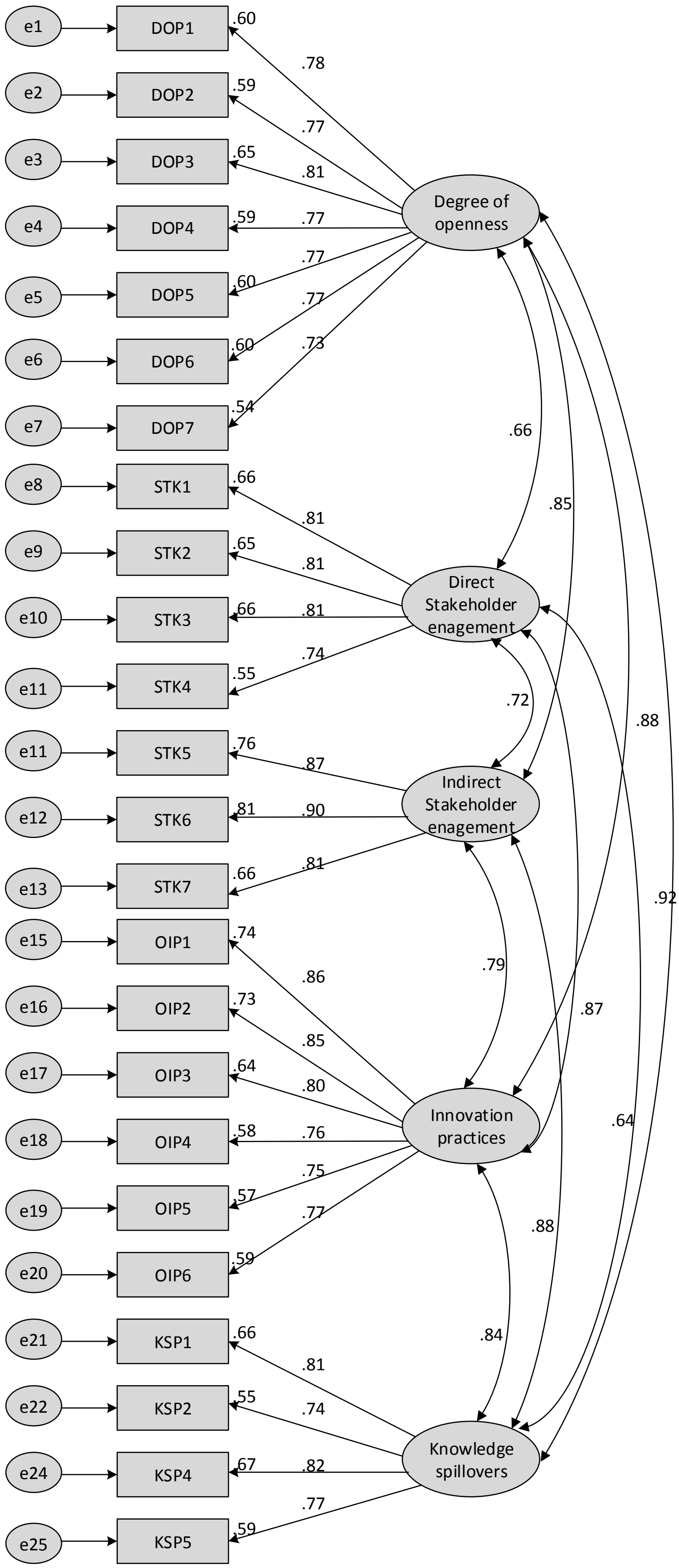

Figure 6.10: Full Measurement Model for Technical Inputs and Business Models Constructs

Table 6.20: Goodness of Fit Statistics and Validity Measures for Value Proposition Constructs

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	1629.682(0.00)	RMSEA	0.04	CFI	0.93	PCFI	0.81
DF	726	RMR	0.05	IFI	0.93	PNFI	0.80
X^2/df	2.245	SRMR	0.05	TLI	0.92	Pclose	1.00

Factor loadings

Factor	CR	AVE	Item	SFL	SMC	Comment
DOP	0.91	0.60	DOP1	0.77	0.60	
			DOP2	0.78	0.61	
			DOP3	0.79	0.63	
			DOP4	0.76	0.58	
			DOP5	0.76	0.58	
			DOP6	0.77	0.59	
			DOP7	0.76	0.58	
Direct STK	0.87	0.62	STK1	0.80	0.64	
			STK2	0.82	0.67	
			STK3	0.80	0.64	
			STK4	0.74	0.55	
Indirect STK	0.89	0.74	STK5	0.87	0.75	
			STK6	0.89	0.80	
			STK7	0.82	0.68	
OIP	0.91	0.64	OIP1	0.86	0.74	
			OIP2	0.85	0.73	
			OIP3	0.80	0.64	
			OIP4	0.76	0.58	
			OIP5	0.75	0.57	
			OIP6	0.77	0.59	
KSP	0.86	0.61	KSP1	0.81	0.66	
			KSP2	0.74	0.55	
			KSP3	Deleted		
			KSP4	0.82	0.67	
			KSP5	0.77	0.59	

Model fit is acceptable

The results presented in Table 6.20 suggest an acceptable fit. The normed chi-square value is 2.245. The absolute (RMSEA, RMR and SRMR), incremental (CFI, IFI and TLI) and parsimony (PCFI and PNFI) fit indices were examined and the values were found to be within the acceptable range. The Pclose value of 1.00 also suggests a good model fit. The SFL are greater than 0.7, the SMC are greater than 0.4 and the CR values are greater than 0.7 (Hair et al. 2010). The SFL, SMC and CR values provide evidence of convergent validity. The GOF values in Table 6.20 suggest that the proposed full model is admissible.

On examining the model fit statistics and establishing convergent validity, further tests were conducted to establish discriminant validity. The chi-square difference tests were conducted for the constructs presented in the full model (see Figure 6.10). The constructs in this domain were taken in pairs and CFA performed with and without correlating the constructs degree of openness, direct stakeholder engagement, indirect stakeholder engagement, innovation practices and knowledge spill-overs. In line with the suggestions made by Segars (1997) and Zaid & Bertea (2011), the chi-square difference test was conducted to assess discriminant validity. The results, presented in Table 6.21, indicate that the chi-square difference tests are significant, suggesting discriminant validity.

Table 6.21: Discriminant Validity of Technical Inputs Constructs

Construct		CR	AVE	Degree of Openness			Direct stakeholders			Indirect stakeholders			Innovation practices			Knowledge spillovers		
				X^2	Df	P	X^2	Df	P	X^2	Df	P	X^2	Df	P	X^2	Df	P
Degree of Openness	Correlation set free						856.593	132	0.000	582.6	105	0.000	965.383	132	0.000	996.635	132	0.000
	Correlation						328.502	129	0.000	270.671	102	0.000	434.326	129	0.000	278.861	129	0.000
	Difference	0.90	0.60				528.091	3		311.929	3		531.057	3		717.774	3	
Direct stakeholders	Correlation set free			856.593	132	0.000				510.492	42	0.000	664.577	105	0.000	658.86	60	0.000
	Correlation			328.502	129	0.000				142.3	39	0.000	196.578	102	0.000	88.225	57	0.005
	Difference	0.87	0.62	528.091	3					368.192	3		570.635	3		570.635	3	
Indirect stakeholders	Correlation set free			582.6	105	0.000	510.492	42	0.000				844.24	81	0.000	334.891	42	0.000
	Correlation			270.671	102	0.000	142.3	39	0.000				159.181	78	0.000	64.541	39	0.000
	Difference	0.90	0.74	311.929	3		368.192	3					685.059	3		270.35	3	
Innovation practices	Correlation set free			965.383	132	0.000	664.577	105	0.000	844.24	81	0.000				813.893	105	0.000
	Correlation			434.326	129	0.000	196.578	102	0.000	159.181	78	0.000				219.29	102	0.000
	Difference	0.91	0.64	531.057	3		685.059	3		685.059	3					594.603	3	
Knowledge spillovers	Correlation set free			996.635	132	0.000	658.86	60	0.000	334.891	42	0.000	813.893	105	0.000			
	Correlation			278.861	129	0.000	88.225	57	0.005	64.541	39	0.000	219.29	102	0.000			
	Difference	0.86	0.61	717.774	3		570.635	3		270.35	3		594.603	3				

6.5.7 Measurement Models for Open Innovation and Economic Outputs

Congeneric Measurement Model for Inbound Innovation Construct

The inbound innovation construct was hypothesised to consist of three items. The CFA results of the proposed one-factor congeneric measurement model are presented in Figure 6.11.

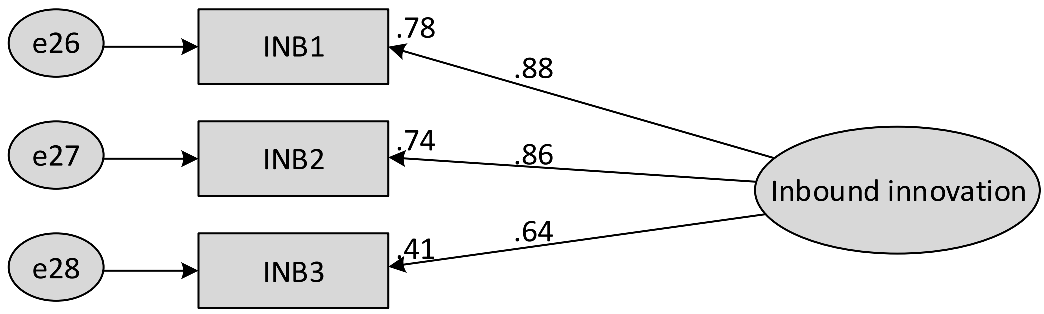

Figure 6.11: First-Order Measurement Model for Inbound Innovation

The proposed model for inbound innovation is identified with a chi-square value of 22.90 and 6 degrees of freedom. The normed chi-square (X^2/df) value of 3.817 is within the range 3–5. Scholars (Hair et al. 2010, p. 648; Wheaton et al. 1977 as cited in Hooper, Coughlan & Mullen 2008, p. 54) explain that the X^2 test can be used for statistical significance. The chi-square test presents trade-offs for researchers: although low X^2 values are desirable, it should not be detrimental to the overall validity of the model (Hair et al. 2010). The normed chi-square values below 5 are considered appropriate and values below 3 are considered excellent (Bagozzi, Yi & Phillips 1991 as cited in Lewis, Byrd & Templeton 2005).

The RMSEA and SRMR values of 0.064 and 0.014 suggest a good model fit. However, the RMR value of 0.13 is above the threshold of 0.09. Hooper, Coughlan and Mullen (2008) indicate that the RMR value is dependent on the scales of each indicator and low values indicate a good fit. Since the RMR values may vary with scales of each indicator, they suggest using SRMR values in case of high RMR values. The SRMR value of 0.01 is closer to 0, which indicates a perfect fit. The incremental fit index (CFI, IFI and TLI) values are above 0.97. The parsimony fit index and Pclose values are within the acceptable range. The results indicate that the proposed model is a good fit. Evidence of construct validity exists if the SFL and SMC values are above 0.5 (preferably 0.7) and 0.3 (preferably 0.5). The SFLs for INB1, INB2 and INB3 are above 0.6 and the SMC values are above 0.3. These values establish construct validity (Hair et al. 2010). Table 6.22 presents statistics for the proposed one-factor model for inbound innovation.

Table 6.22: Goodness of Fit Statistics and Validity Measures for Inbound Innovation

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	22.90(0.00)	RMSEA	0.06	CFI	0.98	PCFI	0.65
DF	6	RMR	0.13	IFI	0.98	PNFI	0.650
X^2/df	3.817	SRMR	0.01	TLI	0.97	Pclose	0.18

Factor loadings
($P < 0.001$***, $P < 0.01$**, $P < 0.05$*)

Item	SE	CR	P	SMC	Comment
INB1	0.88	25.942	***	0.78	Model is identified
INB2	0.86	25.170	***	0.74	
INB3	0.64	17.641	***	0.41	

Model fit is acceptable

Congeneric Measurement Model for Outbound Innovation Construct

The outbound innovation construct was hypothesised to consist of seven items. However, the items OUB4 (*Our organisation cooperates with other organisations and supports their projects to gain access to their knowledge/technology*) and OUB7 (*Our organisation is willing to enter into partnerships to introduce and promote news products and services*) were deleted during the EFA because of cross-loadings with the innovation performance construct. The CFA results of the proposed one-factor congeneric measurement model are presented in Figure 6.12.

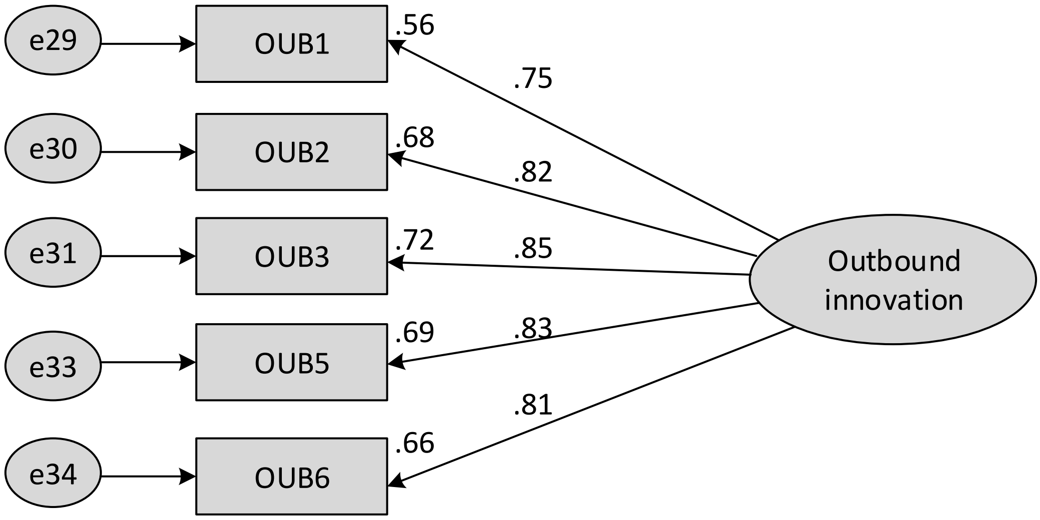

Figure 6.12: First-Order Measurement Model for Outbound Innovation

The proposed model for outbound innovation is identified with a chi-square value of 134.507 and 15 degrees of freedom with a probability level of 0.000. The normed chi-square value of 8.967 is well above the threshold of 5. Hair et al. (2010) explain that chi-square (X^2) may increase with sample size and greater number of observed variables. Although the RMSEA value of 0.8 is preferred, a value of 0.1 is still considered acceptable (Hair et al. 2010; Lewis, Byrd & Templeton 2005). Hence, an RMSEA value of 0.10 is accepted. The RMR and SRMR values of 0.056 and 0.04 are within the acceptable range. The CFI and IFI values are above 0.95, but the TLI value is below 0.90. The parsimony fit index (PCFI and PNFI) values are slightly below the expected values of greater than 0.5. The SFLs for OUB1, OUB2, OUB3, OUB5 and OUB6 are above 0.7 and the SMC values are above 0.50. Table 6.23 presents statistics for the proposed one-factor model for outbound innovation. The results indicate that the presented model is not admissible.

Table 6.23: Goodness of Fit Statistics and Validity Measures for Outbound Innovation

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	134.507(0.00)	RMSEA	0.10	CFI	0.95	PCFI	0.47
DF	15	RMR	0.06	IFI	0.95	PNFI	0.47
X^2/df	8.967	SRMR	0.04	TLI	0.89	Pclose	0.00

Factor loadings
($P < 0.001$***, $P < 0.01$**, $P < 0.05$*)

Item	SE	CR	P	SMC	Comment
OUB1	0.75	11.271	***	0.56	Model is not identified
OUB2	0.82	9.937	***	0.68	
OUB3	0.85	9.294	***	0.72	
OUB5	0.83	10.006	***	0.69	
OUB6	0.81	10.088	***	0.66	

Model fit is inadmissible

To improve model fit, the standardised residual covariances and modification indices were checked. The standardised residuals can be obtained by dividing raw residuals by the standard error of the residuals. Residual covariances describe the errors between the predicted covariances and the sample covariance matrix. Hair et al. (2010, p. 649) explain that ‘the error in prediction for each covariance term creates a residual’. The average standardised residual (SR) value is zero and the value can be positive or negative. The individual residuals help researchers to pinpoint potential issues with the model. With the correct model, standardised residual covariances have a standard normal distribution and a value less than 2 (Jöreskog & Sörbom 1984). Hair et al. (2010) point out that SR values outside the range −4 to 4 indicate potential problems.

Modification indices explain the approximate increase in chi-square if the parameter were free. It is calculated for every possible relationship that is not estimated in a model. Modification indices of 4 and above suggest respecification of the model by freeing the corresponding path to be estimated (Hair et al. 2010).

Table 6.24: Respecification Statistics for Outbound Innovation

Standardised residual covariances						Modification indices				
									M.I.	Par change
	OUB6	OUB5	OUB3	OUB2	OUB1	e31	<-->	e34	27.688	0.176
OUB6	0					e31	<-->	e33	7.991	-0.090
OUB5	0.202	0				e30	<-->	e34	21.715	-0.148
OUB3	1.091	-0.555	0			e30	<-->	e33	4.571	0.065
OUB2	-1.065	0.462	-0.178	0		e29	<-->	e34	5.879	-0.080
OUB1	-0.687	0.015	-0.414	1.123	0	e29	<-->	e30	16.814	0.123
						e33	<-->	e34	14.881	0.126

Table 6.24 presents residual covariances for all the variables. This table provides differences between the sample variance/covariances, and the estimated population variance. The residuals relating to OUB6 are distressingly large as per the range suggested by Jöreskog and Sörbom (1984). We might want to modify the model to reduce these residuals. Hair et al. (2010) suggest using residual diagnostics to modify the model after reviewing modification indices. Modification index of 27.688 indicates that the chi-square value would improve 27.688 units if e31 and e34 were covaried. Par change of 0.176 is an approximate value for the suggested covariance between e31 and e34.

Modification index of 14.881 indicates that the chi-square value would improve 14.881 units if e33 and e34 were covaried. Par change of 0.126 is an approximate value for the suggested covariance between e33 and e34. Modification indices and par changes for covariances e29 and e30 are presented in Table 6.25. These results indicate relevance between the items OUB3, OUB5 and OUB6.

Although the use of modification indices to covary the items would free the corresponding path to be estimated, Hair et al. (2010) point out that model changes solely based on modification indices are not advisable unless there is theoretical support. The items for the outbound innovation construct were taken from previous studies where these items were used either individually or grouped with inbound innovation.

The literature offers three ways to respecify a model (Hair et al. 2010; Holmes-Smith 2007). The first approach is to delete items with low factor loadings. Items with factor loadings less than 0.40 are considered minimum, factor loadings above 0.50 are considered practically significant, and factor loadings of above 0.70 are indicative of a well-defined structure. Hair et al. (2010) suggest guidelines for identifying significant factor loadings based on sample size. For a sample of 250–349, the significant factor loading would be 0.35. Therefore, items with the factor loading above 0.35 are considered acceptable. The second approach is to covary items to free the corresponding path to be estimated. The third approach is to load items that covary too highly onto a new factor, but this requires theoretical support. The SFLs for OUB1, OUB2, OUB3, OUB5 and OUB6 are above 0.7 and the SMC values are above 0.5. Based on the modification indices, items e31 and e34 were covaried. To improve the model further, e33 and e34 were covaried. Figure 6.13 shows the covariances, SFLs and SMC values.

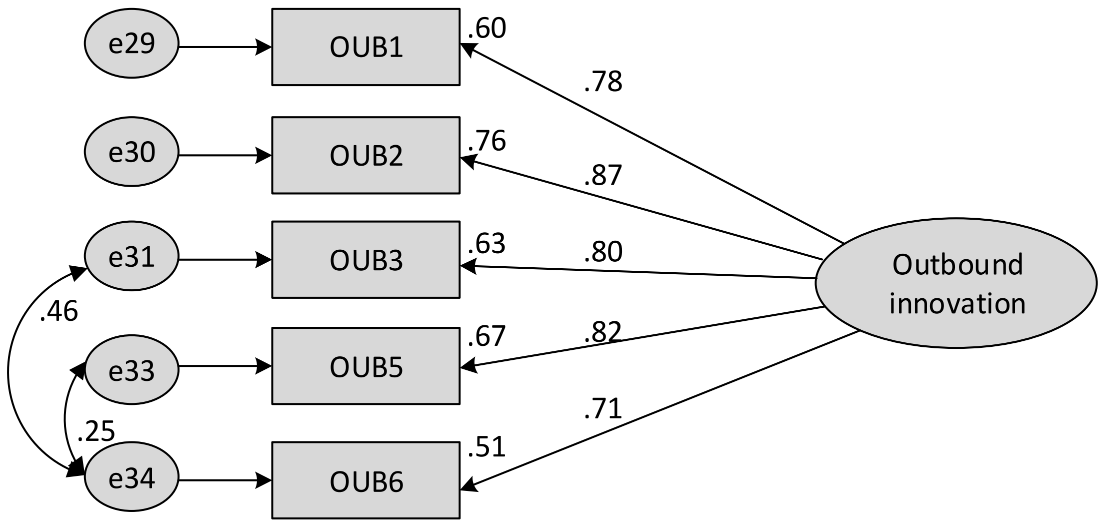

Figure 6.13: First-Order Measurement Model for Outbound Innovation (Respecified)

The results relating to GOF statistics for the respecified model are presented in Table 6.26. The respecified model for outbound innovation is identified with a chi-square value of 19.878 and 9.019 degrees of freedom with a probability level of 0.019. The normed chi-square value of 2.209 is well below the threshold of 5. Though a RMSEA value of 0.8 is preferred, a value of 0.1 is still considered acceptable (Hair et al. 2010; Lewis, Byrd & Templeton 2005). The RMSEA value in the respecified model has improved significantly. The RMSEA, RMR and SRMR values of 0.04, 0.03 and 0.01 indicate good model fit. The incremental fit index (CFI, IFI and TLI) values also improved. The TLI value 0.98 is well above the threshold. The Pclose value (0.67) also improved. However, the parsimony fit index (PCFI and PNFI) values dropped from 0.47 and 0.47 to 0.3 and 0.3 respectively. Hair et al. (2010) explain that the parsimony ratio is calculated by comparing the degrees of freedom (df) used by a model to the available degrees of freedom. Any attempts to improve PCFI and PNFI values can increase the normed chi-square value. Hence, the use of parsimony fit indices remains controversial to some extent. Therefore, no further action has been taken to achieve higher PCFI and PNFI values. The SFLs for OUB1, OUB2, OUB3, OUB5 and OUB6 are above 0.7 and the SMC values are above 0.50. Table 6.25 presents statistics for the proposed one-factor model for outbound innovation. The results indicate that the model is admissible.

Table 6.25 Goodness of Fit Statistics and Validity Measures for Outbound Innovation (Respecified)

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X²	19.878(0.01)	RMSEA	0.04	CFI	0.99	PCFI	0.30
DF	9.019	RMR	0.03	IFI	0.99	PNFI	0.30
X²/df	2.209	SRMR	0.01	TLI	0.98	Pclose	0.67

Factor loadings
($P < 0.001$***, $P < 0.01$**, $P < 0.05$*)

Item	SE	CR	P	SMC	Comment
OUB1	0.78	10.692	***	0.60	Model is identified
OUB2	0.87	7.807	***	0.76	
OUB3	0.80	10.275	***	0.63	
OUB5	0.82	9.702	***	0.67	
OUB6	0.71	11.541	***	0.51	

Model fit is admissible

Congeneric Measurement Model for Innovation Performance Construct

The innovation performance construct was hypothesised to consist of four items. The CFA results of the proposed one-factor congeneric measurement model are presented in Figure 6.14.

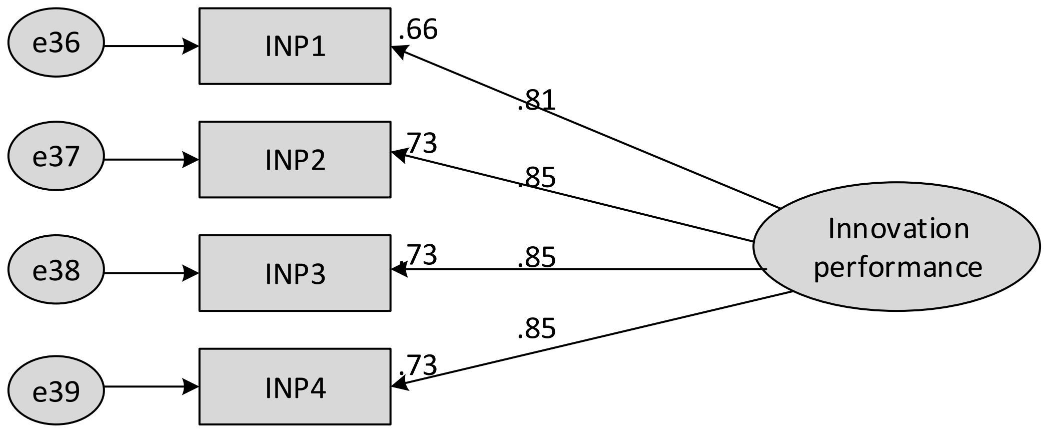

Figure 6.14: First-Order Measurement Model for Innovation Performance

The proposed model for innovation performance is identified with a chi-square value of 31.609 and 6 degrees of freedom. The normed chi-square value of 5.268 suggests poor fit. The other absolute fit index (RMSEA, RMR and SRMR) values are 0.07, 0.02 and 0.02 respectively, within the specified range. The incremental fit index (CFI, IFI and TLI) values are above 0.96. The standardised estimates for INP1, INP2, INP3 and INP4 are above 0.8. The SMC values are above 0.65 and the Pclose value is 0.034. However, the parsimony fit index (PCFI and PNFI) values of 0.329 and 0.327 raise concerns. The results presented in Table 6.26 indicates that this model is not admissible.

Table 6.26: Goodness of Fit Statistics and Validity Measures for Innovation Performance

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	31.609(0.5)	RMSEA	0.07	CFI	0.99	PCFI	0.33
DF	6	RMR	0.02	IFI	0.99	PNFI	0.33
X^2/df	5.268	SRMR	0.02	TLI	0.96	Pclose	0.03

Factor loadings
($P < 0.001$***, $P < 0.01$**, $P < 0.05$*)

Item	SE	CR	P	SMC	Comment
INP1	0.81	10.315	***	0.66	
INP2	0.85	9.304	***	0.73	
INP3	0.85	9.196	***	0.73	
INP4	0.85	9.356	***	0.73	

Model fit is inadmissible

To improve model fit, the standardised residual covariances and modification indices were checked. Hair et al. (2010, p. 649) explain that the individual residuals help researchers to pinpoint potential issues with the model. With the correct model, standardised residual covariances have a standard normal distribution and a value less than 2 (Jöreskog & Sörbom 1984).

Modification indices explain the approximate increase in chi-square if the parameter were free. It is calculated for every possible relationship that is not estimated in a model. Modification indices of 4 and above suggest respecification of the model by freeing the corresponding path to be estimated (Hair et al. 2010).

Table 6.27: Respecification Statistics for Innovation Performance

	Standardised residual covariances				Modification Indices				
								M.I.	Par Change
	INP4	INP3	INP2	INP1	e37	<-->	e39	5.494	0.045
INP4	.000				e36	<-->	e38	7.031	0.049
INP3	-.198	.000							
INP2	.413	-.210	.000						
INP1	-.283	.538	-.261	.000					

Table 6.27 presents residual covariances for all variables in the innovation performance construct. This table provides differences between the sample variance/covariances, and the estimated population variance. The residuals relating to INP3 are comparatively large as per the range suggested by Jöreskog and Sörbom (1984). These can be used as a guide to modify the model to reduce these residuals. Hair et al. (2010) suggest using residual diagnostics to modify the model after reviewing modification indices. Modification index of 7.031 indicates that the chi-square value would improve 0.049 units if e36 and e38 were covaried. Par change of 0.049 is an approximate value for the suggested covariance between e36 and e38.

The modification indices and par changes for covariances e37 and e39 are presented in Table 6.28. These results indicate relevance between the items INP1 and INP3. Although the use of modification indices to covary the items would free the corresponding path to be estimated, Hair et al. (2010) indicate that model changes solely based on modification indices are not advisable unless there is theoretical support. The items for innovation performance were adapted from previous studies where these items were used either individually or grouped with other performance indicators. In line with the approach proposed by Hair et al. (2010) and Holmes-Smith (2007), the two items INP1 and INP3 were covaried. Figure 6.15 shows the covariances, SFLs and SMC values.

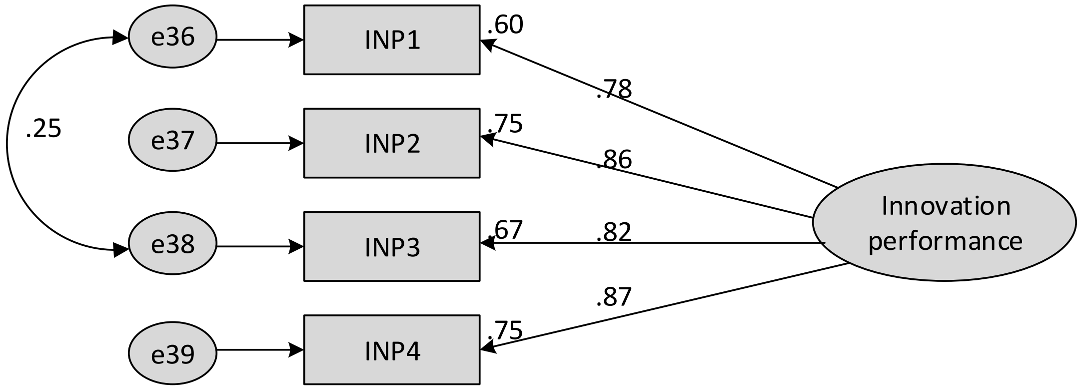

Figure 6.15: First-Order Measurement Model for Innovation Performance (Respecified)

The results relating to GOF statistics for the respecified model are presented in Table 6.28. The respecified model for innovation performance is identified with a chi-square value of 16.265 and 11 degrees of freedom. The normed chi-square value of 1.479 is well below the threshold of 5. The absolute and incremental fit indices and Pclose values indicate good model fit. The parsimony fit index (PCFI and PNFI) values improved from 0.33 and 0.33 to 0.61 and 0.61 respectively. Hair et al. (2010) highlight that any attempts to improve PCFI and PNFI values can increase the normed chi-square value. Hence, the use of parsimony fit indices remains controversial to some extent. Therefore, no further action has been taken to achieve higher PCFI and PNFI values. The SLFs for INP1, INP2, INP3 and INP4 are above 0.7 and the SMC values are above 0.50. Table 6.28 presents statistics for the proposed one-factor model for innovation performance. The results indicate that the presented model is admissible.

Table 6.28: Goodness of Fit Statistics and Validity Measures for Innovation Performance (Respecified)

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	16.265(0.1)	RMSEA	0.02	CFI	0.98	PCFI	0.61
DF	11	RMR	0.00	IFI	0.99	PNFI	0.61
X^2/df	1.479	SRMR	0.00	TLI	0.99	Pclose	0.94

Factor loadings
($P < 0.001$***, $P < 0.01$**, $P < 0.05$*)

Item	SE	CR	P	SMC	Comment
INP1	0.78	23.065	***	0.60	Model is identified
INP2	0.86	27.217	***	0.75	
INP3	0.82	24.834	***	0.67	
INP4	0.87	27.622	***	0.75	
Model fit is admissible					

Full Measurement Model for Open Innovation and Economic Output Constructs

This section presents the validity of the three constructs forming the open innovation and economic outputs domains. Section 6.5.7 presented the congeneric measurement models for open innovation and economic outputs constructs. All the constructs in these domains were individually examined and validated.

Figure 6.16 shows the full measurement model for the open innovation and economic outputs domains. Table 6.29 presents results associated with construct validity and GOF statistics.

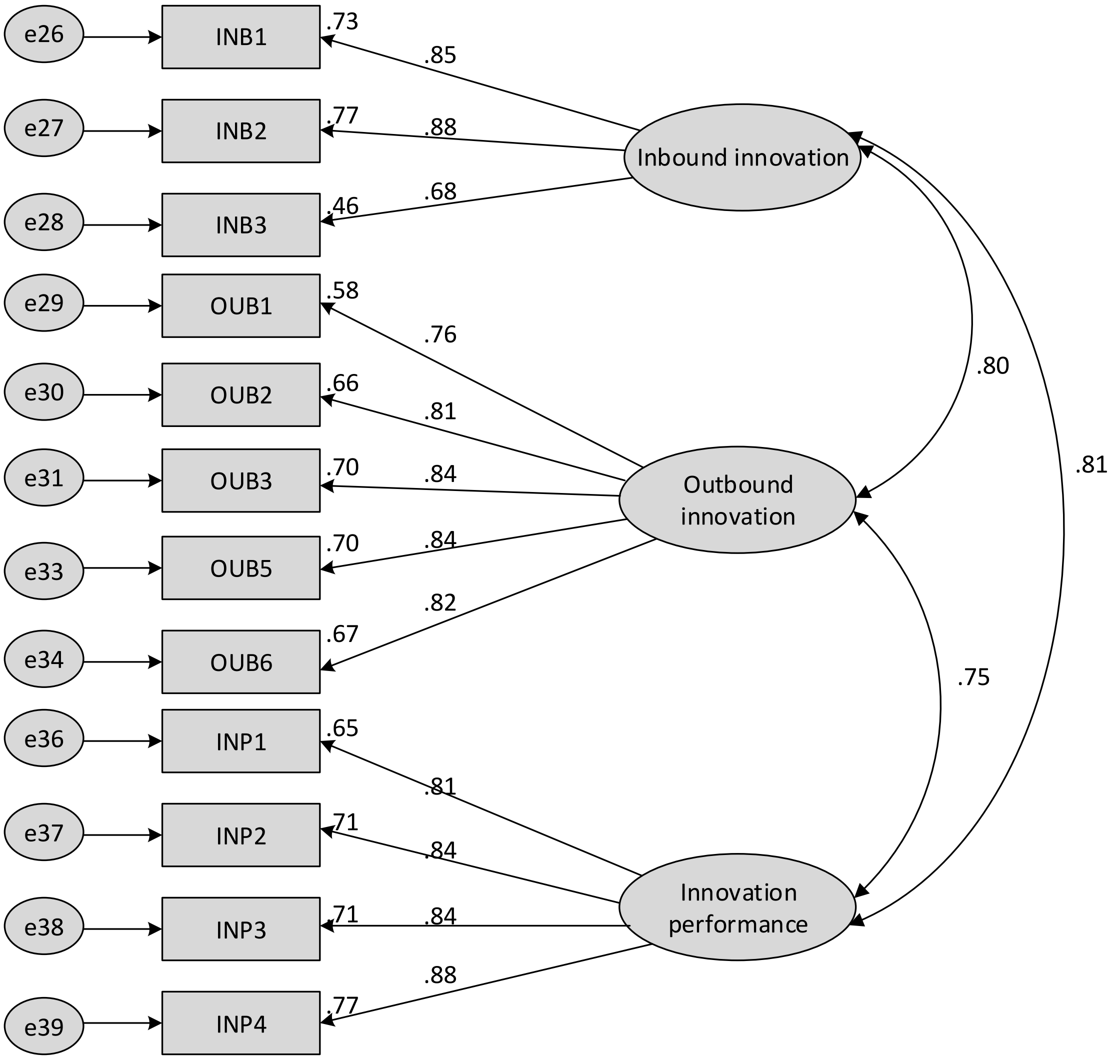

Figure 6.16: Full Measurement Model for Open Innovation and Economic Outputs

The proposed full measurement model for the open innovation and economic outputs domain is identified with a chi-square value of 525.812 and 153 degrees of freedom. The normed chi-square value of 3.437 is well below 5. The absolute fit index (RMSEA, RMR and SRMR) values are 0.06, 0.06 and 0.06 respectively, within the specified range. The incremental fit index (CFI, IFI and TLI) values are above 0.92. The standardised estimates for all the items are above 0.7, except for INB3, which is 0.68. The SMC values are above 0.4 and the Pclose value is 0.003. The parsimony fit index (PCFI and PNFI) values are 0.73 and 0.71.

Table 6.29: Goodness of Fit Statistics and Validity Measures for Open Innovation and Economic Outputs Constructs

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	525.812 (0.00)	RMSEA	0.06	CFI	0.94	PCFI	0.73
DF	153	RMR	0.06	IFI	0.94	PNFI	0.71
X^2/df	3.437	SRMR	0.06	TLI	0.92	Pclose	0.003

Factor loadings
(P < 0.001***, P < 0.01**, P < 0.05*)

Factor	CR	AVE	Item	SFL	SMC	Comment
INB	0.91	0.67	INB1	0.85	0.73	X^2/df value is 3.47 and it is possible to improve this value.
			INB2	0.88	0.77	
			INB3	0.68	0.46	
OUB	0.85	0.65	OUB1	0.76	0.58	
			OUB2	0.81	0.66	
			OUB3	0.84	0.70	
			OUB4	Item deleted		
			OUB5	0.84	0.70	
			OUB6	0.82	0.67	
			OUB7	Item deleted		
INNP	0.91	0.71	INP1	0.81	0.65	
			INP2	0.84	0.71	
			INP3	0.84	0.71	
			INP4	0.88	0.77	

Model can be re-estimated

The results in Table 6.29 indicate that this model is not admissible. However, on examining modification indices presented in Table 6.30, it was found that the chi-square value would improve by modifying the model. Modification index of 28.456 indicates that the chi-square value would improve 0.177 units if e31 and e34 were covaried. Par change of 0.177 is an approximate value for the suggested covariance between e31 and e34. As suggested by Hair et al. (2010), the two items OUB3 and OUB6 were covaried.

Table 6.30: Modification Indices for the Full Measurement Model for Open Innovation and Economic Outputs

Modification Indices				
			M.I.	Par Change
e29	<-->	e30	15.580	0.117
e31	<-->	e34	28.456	0.177

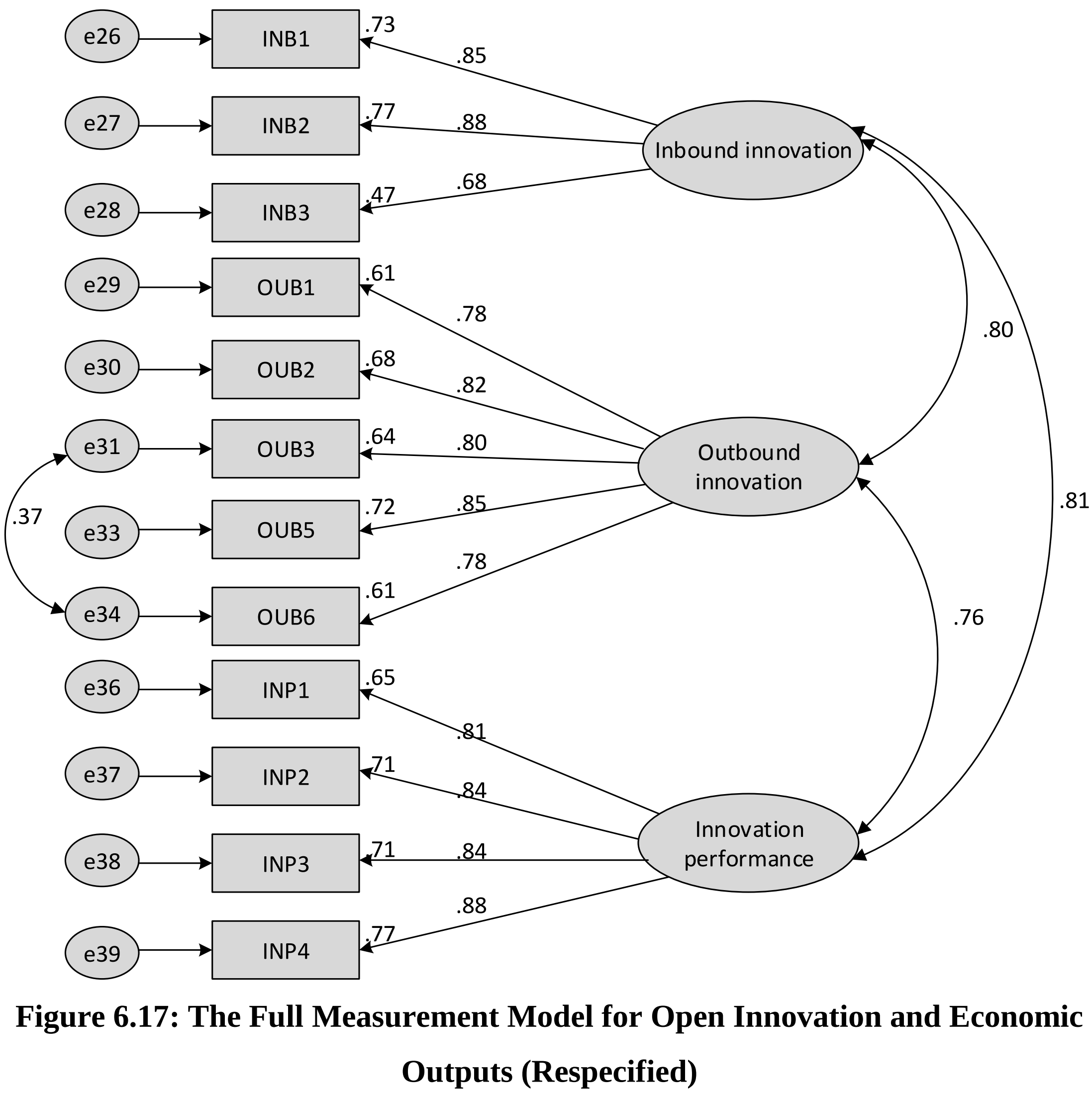

Figure 6.17: The Full Measurement Model for Open Innovation and Economic Outputs (Respecified)

Figure 6.17 shows the covariances, SFLs and SMC values. The results in Table 6.31 suggest an acceptable fit. The normed chi-square value is 3.03. The absolute (RMSEA, RMR and SRMR), incremental (CFI, IFI and TLI) and parsimony (PCFI and PNFI) fit indices were examined and the values were found to be within the acceptable range. The SFLs are greater than 0.5. The SMC are greater than 0.4 and the CR values are greater than 0.7 (Hair et al. 2010). The SFL, SMC and CR values provide evidence of convergent validity. The GOF values in Table 6.31 suggest that the proposed full model is admissible.

Table 6.31: Goodness of Fit Statistics and Validity Measures for Open Innovation Economic Outputs Constructs (respecified)

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	455.214 (0.00)	RMSEA	0.05	CFI	0.95	PCFI	0.72
DF	150	RMR	0.05	IFI	0.95	PNFI	0.70
X^2/df	3.03	SRMR	0.05	TLI	0.94	Pclose	0.10

Factor loadings
($P < 0.001$***, $P < 0.01$**, $P < 0.05$*)

Factor	CR	AVE	Item	SFL	SMC	Comment
INB	0.85	0.65	INB1	0.85	0.73	
			INB2	0.88	0.77	
			INB3	0.68	0.47	
OUB	0.90	0.65	OUB1	0.78	0.61	
			OUB2	0.82	0.66	
			OUB3	0.80	0.4	
			OUB4	Item deleted		
			OUB5	0.85	0.72	
			OUB6	0.78	0.61	
			OUB7	Item deleted		
INNP	0.90	0.70	INP1	0.81	0.65	
			INP2	0.84	0.71	
			INP3	0.84	0.71	
			INP4	0.88	0.77	

Model fit acceptable

On examining the model fit statistics and establishing convergent validity, further tests were conducted to establish discriminant validity. The chi-square difference tests were conducted for the constructs presented in the full model (see Figure 6.17). The two constructs inbound innovation and outbound innovation from open innovation and innovation performance from economic outputs domains were taken in pairs and CFA performed with and without correlating the constructs. The results in Table 6.32 indicate that the chi-square difference tests are significant, suggesting discriminant validity.

Table 6.32: Discriminant Validity of Open Innovation and Economic Outputs Constructs

Construct		CR	AVE	Inbound innovation			Outbound innovation			Innovation performance		
				X^2	Df	P	X^2	Df	P	X^2	Df	P
Inbound innovation	Correlation set free	0.85	0.65				712.255	60	0.000	651.453	42	0.000
	Correlation						235.968	57	0.000	149.799	39	0.000
	Difference						476.287	3		501.654	3	
Outbound innovation	Correlation set free	0.91	0.61	712.255	60	0.000				761.189	81	0.000
	Correlation			235.968	57	0.000				330.208	78	0.000
	Difference			476.287	3					430.981	3	
Innovation performance	Correlation set free	0.90	0.79	651.453	42	0.000	761.189	81	0.000			
	Correlation			149.799	39	0.000	330.208	78	0.000			
	Difference			501.654	3		430.981	3				

Congeneric One-factor Measurement Model for Absorptive Capacity Construct

The AC construct was hypothesised to consist of five items. The CFA results of the proposed one-factor congeneric measurement model are presented in Figure 6.18.

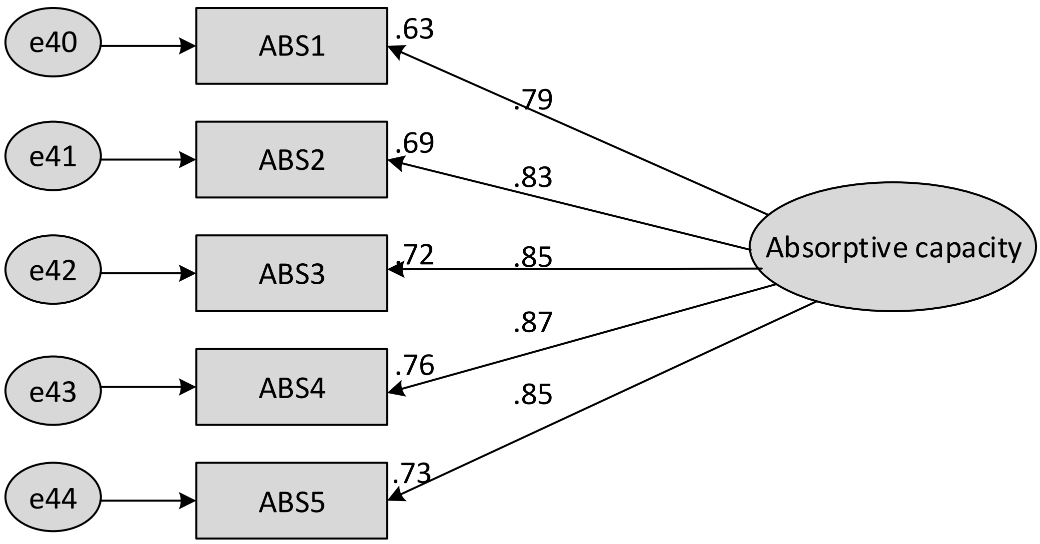

Figure 6.18: First-Order Measurement Model for Absorptive Capacity

The proposed model for AC is identified with a chi-square value of 33.232 and 15 degrees of freedom. The normed chi-square (X^2/df) value of 2.215 is within the 3–5 range. The absolute fit index (RMSEA, RMR and SRMR) values are 0.042, 0.015 and 0.014. The incremental fit index (CFI, IFI and TLI) values are above 0.98. However, the parsimony fit index (PCFI and PNFI) values (0.496 and 0.493) are just below the acceptable range of 0.5. The results indicate that the proposed model is a good fit. Evidence of construct validity exists if the SFL and SMC values are above 0.5 (preferably 0.7) and 0.3 (preferably 0.5). The SFLs for ABS1, ABS2, ABS3, ABS4 and ABS5 are above 0.7 and the SMC values are above 0.5. These values establish construct validity (Hair et al. 2010). Table 6.33 presents statistics for the proposed one-factor model for AC.

Table 6.33: Goodness of Fit Statistics and Validity Measures for Absorptive Capacity

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	33.232(0.004)	RMSEA	0.04	CFI	0.99	PCFI	0.5
DF	15	RMR	0.01	IFI	0.99	PNFI	0.5
X^2/df	2.215	SRMR	0.01	TLI	0.99	Pclose	0.730

Factor loadings
(P < 0.001***, P < 0.01**, P < 0.05*)

Item	SE	CR	P	SMC	Comment
ABS1	0.79	11.277	***	0.63	Model is identified
ABS2	0.83	10.604	***	0.69	
ABS3	0.5	10.271	***	0.72	
ABS4	0.87	9.615	***	0.76	
ABS5	0.85	10.117	***	0.73	
Model fit is admissible					

Full Measurement Model for Open Innovation and Economic Outputs Constructs with Absorptive Capacity

This section presents the validity of the three constructs forming the open innovation and economic outputs domains and their convergence with the AC construct. Section 6.5.7 presented the congeneric measurement models for the OI and economic outputs domains and AC constructs. All the constructs in these two domains were individually examined and validated.

Figure 6.19 shows the full measurement model for the open innovation and economic outputs domains and AC. Table 6.34 presents results associated with construct validity and GOF statistics.

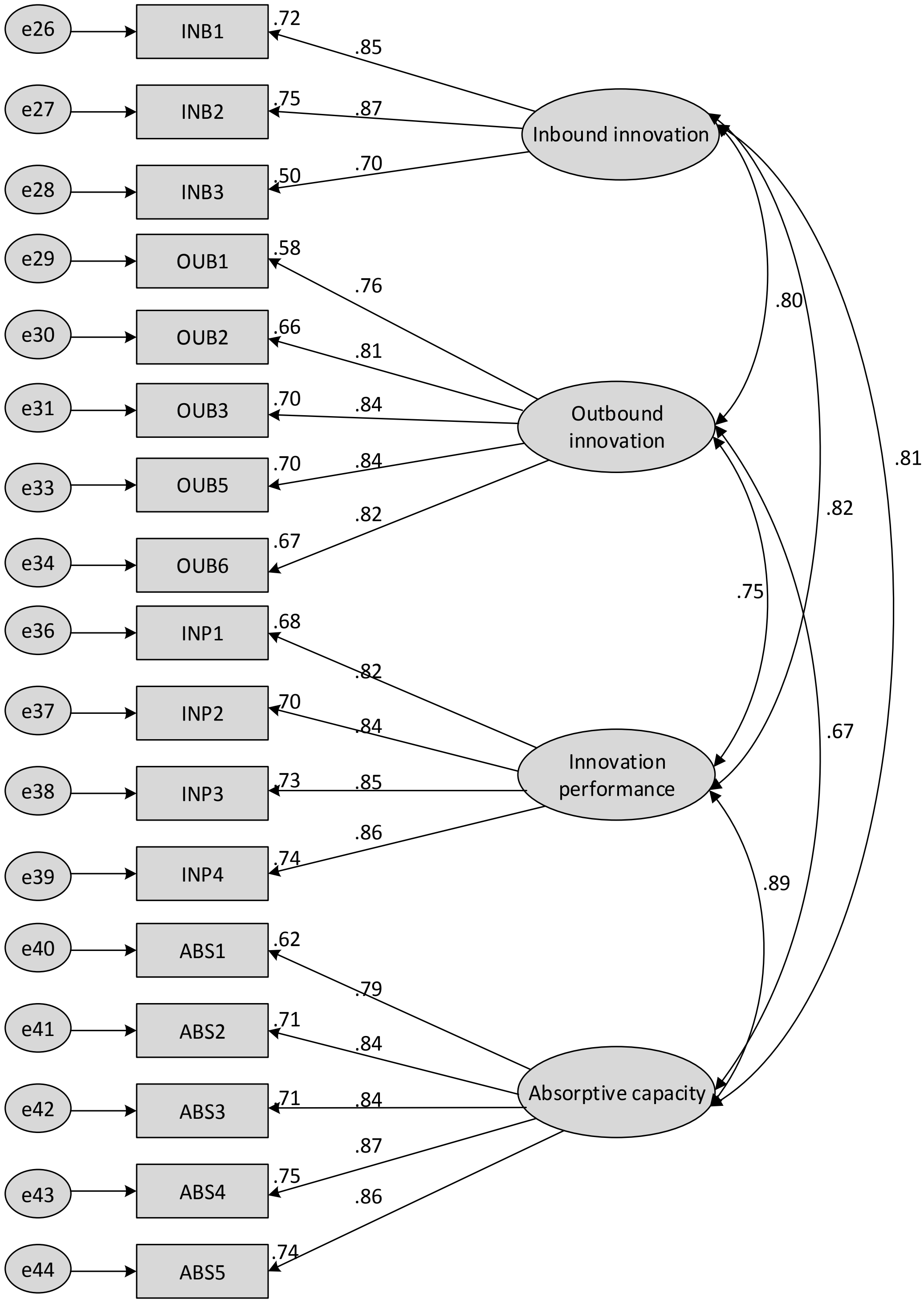

Figure 6.19: Full Measurement Model for Open Innovation and Economic Outputs with Absorptive Capacity

Table 6.34: Goodness of Fit Statistics and Validity Measures for Open Innovation and Economic Outputs Constructs with Absorptive Capacity

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	907.756(0.00)	RMSEA	0.05	CFI	0.94	PCFI	0.78
DF	339	RMR	0.05	IFI	0.94	PNFI	0.76
X^2/df	2.678	SRMR	0.05	TLI	0.93	Pclose	0.60

Factor loadings

Factor	CR	AVE	Item	SFL	SMC	Comment
INB	0.85	0.65	INB1	0.85	0.72	
			INB2	0.87	0.75	
			INB3	0.70	0.50	
OUB	0.91	0.63	OUB1	0.76	0.58	
			OUB2	0.81	0.66	
			OUB3	0.84	0.70	
			OUB4	Item deleted		
			OUB5	0.84	0.70	
			OUB6	0.82	0.67	
			OUB7	Item deleted		
INNP	0.91	0.71	INP1	0.82	0.68	
			INP2	0.84	0.70	
			INP3	0.85	0.73	
			INP4	0.86	0.74	
ABS	0.92	0.70	ABS1	0.79	0.62	
			ABS2	0.84	0.71	
			ABS3	0.84	0.71	
			ABS4	0.87	0.75	
			ABS5	0.86	0.74	
Model fit acceptable						

The results in Table 6.34 suggest an acceptable fit. The proposed full measurement model for open innovation and economic outputs domains with AC are identified with a chi-square value of 907.556 and 339 degrees of freedom. The normed chi-square value of 2.678 is well within the range of 5. The other absolute fit index (RMSEA, RMR and SRMR) values are 0.049, 0.057 and 0.053 respectively, within the specified range. The incremental fit index (CFI, IFI and TLI) values are above 0.92. The standardised estimates for all the items are 0.7 or above. The SMC values are 0.5 or above and the Pclose value is 0.603. The parsimony fit index (PCFI and PNFI) values are 0.782 and 0.755 respectively.

The SFLs are greater than 0.5. The SMC are greater than 0.4 and the CR values are greater than 0.7 (Hair et al. 2010). The SFL, SMC and CR values provide evidence of convergent validity. The GOF values in Table 6.34 suggest that the proposed full model is admissible.

On examining the model fit statistics and establishing convergent validity, further tests were conducted to establish discriminant validity. The chi-square difference tests were conducted for the constructs presented in the full model (see Figure 6.19). The three constructs inbound innovation, outbound innovation and innovation performance in the two domains (open innovation and economic outputs) and AC were taken in pairs and CFA performed with and without correlating the constructs. The results presented in Table 6.35 indicate that the chi-square difference tests are significant, suggesting discriminant validity.

Table 6.35: Discriminant Validity of Open Innovation and Economic Outputs Constructs with Absorptive Capacity

Construct		CR	AVE	Inbound innovation			Outbound innovation			Innovation performance			Absorptive capacity		
				X^2	Df	P	X^2	Df	P	X^2	Df	P	X^2	Df	P
Inbound innovation	Correlation set free	0.85	0.65				712.255	60	0.000	651.453	42	0.000	702.907	60	0.000
	Correlation						235.968	57	0.000	149.799	39	0.000	187.707	57	0.000
	Difference						476.287	3		501.654	3		515.2	3	
Outbound innovation	Correlation set free	0.91	0.61	712.255	60	0.000				761.189	81	0.000	657.029	105	0.000
	Correlation			235.968	57	0.000				330.208	78	0.000	320.095	102	0.000
	Difference			476.287	3					430.981	3		336.934	3	
Innovation performance	Correlation set free	0.9	0.79	651.453	42	0.000	761.189	81	0.000				940.279	81	0.000
	Correlation			149.799	39	0.000	330.208	78	0.000				202.108	78	0.000
	Difference			501.654	3		430.981	3					738.171	3	
Absorptive capacity	Correlation set free	0.92	0.7	702.907	60	0.000	657.029	105	0.000	940.279	81	0.000			
	Correlation			187.707	57	0.000	320.095	102	0.000	202.108	78	0.000			
	Difference			515.2	3		336.934	3		738.171	3				

6.5.8 Full CFA Measurement Model

The earlier sections detailed each construct separately and also presented full measurement models for the technical inputs, business models, open innovation, economic outputs and absorptive capacity domains. The procedures ensured unidimensionality and construct validity through GOF statistics. These models form the basis for the full measurement model presented in this section (see Figure 6.20).

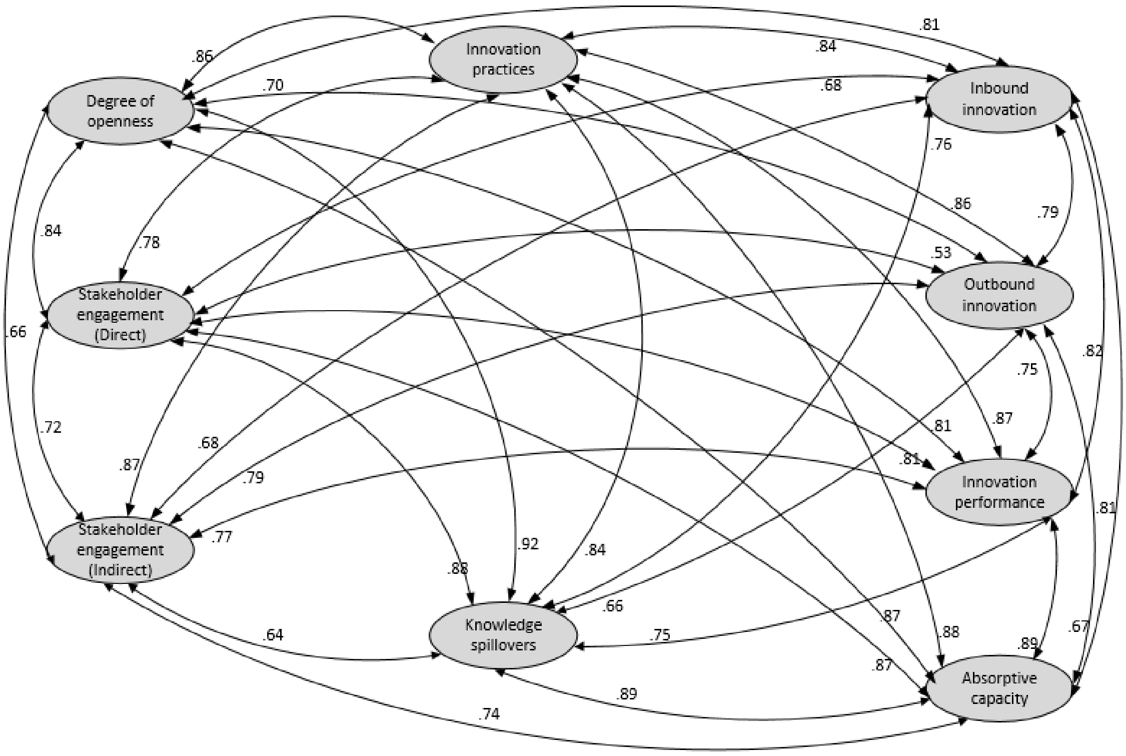

Figure 6.20: Proposed Full CFA Measurement Model

Figure 6.20 presents the constructs and correlations among the constructs. The statistics for the full CFA measurement model are presented in Table 6.36. The normed chi-square value is 2.218. The absolute fit index (RMSEA, RMR and SRMR) values are 0.04, 0.04 and 0.06 respectively. The incremental fit index values are 0.90, except TLI (0.89), and the parsimony fit index values are above 0.5. The Pclose value is 1.00. These results indicate good model fit. Although the TFI value is above 0.80, the preferred value is above 0.90. Table 6.36 presents goodness of fit statistics for the proposed full CFA measurement model.

Table 6.36: Goodness of Fit Statistics for the Proposed Full CFA Measurement Model

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	4851.755(0.00)	RMSEA	0.04	CFI	0.90	PCFI	0.81
DF	2223	RMR	0.06	IFI	0.90	PNFI	0.74
X^2/df	2.183	SRMR	0.05	TLI	0.89	Pclose	1.00

The discriminant validity for the full measurement model is presented in Table 6.38. The correlations between the individual constructs are below 0.90 except for the correlations between the degree of openness and knowledge spill-overs constructs (0.92). The assessment of discriminant validity is considered critical to ensure uniqueness of each construct presented in the full measurement model. As high correlations (above 0.9) between the constructs indicate lack of uniqueness, further tests were carried out to understand the root causes. The item DOP7 was found to be cross-loading with knowledge spill-overs; hence, this item has been deleted. Then, modification indices were checked. Modification indices explain the approximate increase in chi-square if the parameter were free. It is calculated for every possible relationship that is not estimated in a model. Modification indices of 4 and above suggest respecification of the model by freeing the corresponding path to be estimated (Hair et al. 2010).

Table 6.37: Modification Indices for the CFA Full Measurement Model

Modification Indices				
			M.I.	**Par Change**
e24	<-->	e25	5.726	0.050
e26	<-->	e27	8.815	0.072
e30	<->	e31	13.295	0.110

Table 6.37 presents modification indices for the residual covariances for all variables. Hair et al. (2010) suggest using residual diagnostics to modify the model after reviewing modification indices. A modification index of 13.295 indicates that the chi-

square value would improve 13.295 units if e30 and e31 were covaried. Par change of 0.110 is an approximate value for the suggested covariance between e30 and e31. Modification indices and par changes for covariances e24 and e25, e26 and e27, and e30 and e31 are presented in Table 6.40. These results indicate relevance between the items OUB2 and OUB3, KSP4 and KSP5, and INB1 and INB2.

The literature suggests covarying items to free the corresponding path to be estimated (Hair et al. 2010; Holmes-Smith 2007). Although the use of modification indices to covary the items would free the corresponding path to be estimated, Hair et al. (2010) point out that model changes solely based on modification indices are not advisable unless there is theoretical support. The items for knowledge spill-overs, inbound innovation and outbound innovation were taken from previous studies where these items were used either individually or grouped as internal and external participation. Hence, the items presented in Table 6.37 were covaried prior to re-estimating the full measurement model.

Table 6.38: Discriminant Validity for the Proposed Full Measurement Model

Correlations			Estimate	Result (Method 1)
Openness	<-->	Indirect STK	0.66	Discriminant validity holds
Openness	<-->	Direct STK	0.84	Discriminant validity holds
Openness	<-->	Practices	0.88	Discriminant validity holds
Openness	<-->	KSP	0.92	Discriminant validity fails
Openness	<-->	Outbound	0.70	Discriminant validity holds
Openness	<-->	Performance	0.81	Discriminant validity holds
Openness	<-->	Inbound	0.81	Discriminant validity holds
Openness	<-->	Absorptive Capacity	0.87	Discriminant validity holds
Indirect STK	<-->	Direct STK	0.72	Discriminant validity holds
Indirect STK	<-->	Practices	0.87	Discriminant validity holds
Indirect STK	<-->	KSP	0.64	Discriminant validity holds
Indirect STK	<-->	Outbound	0.79	Discriminant validity holds
Indirect STK	<-->	Performance	0.77	Discriminant validity holds
Indirect STK	<-->	Inbound	0.68	Discriminant validity holds
Indirect STK	<-->	Absorptive Capacity	0.74	Discriminant validity holds
Direct STK	<-->	Practices	0.78	Discriminant validity holds
Direct STK	<-->	KSP	0.88	Discriminant validity holds
Direct STK	<-->	Outbound	0.53	Discriminant validity holds
Direct STK	<-->	Performance	0.81	Discriminant validity holds
Direct STK	<-->	Inbound	0.68	Discriminant validity holds
Direct STK	<-->	Absorptive Capacity	0.87	Discriminant validity holds
Practices	<-->	KSP	0.84	Discriminant validity holds
Practices	<-->	Outbound	0.86	Discriminant validity holds
Practices	<-->	Performance	0.87	Discriminant validity holds
Practices	<-->	Inbound	0.84	Discriminant validity holds
Practices	<-->	AbsCapacity	0.88	Discriminant validity holds
KSP	<-->	Outbound	0.66	Discriminant validity holds
KSP	<-->	Performance	0.77	Discriminant validity holds
KSP	<-->	Inbound	0.76	Discriminant validity holds
KSP	<-->	AbsCapacity	0.89	Discriminant validity holds
Outbound	<-->	Performance	0.75	Discriminant validity holds
Outbound	<-->	Inbound	0.79	Discriminant validity holds
Outbound	<-->	AbsCapacity	0.67	Discriminant validity holds
Performance	<-->	Inbound	0.82	Discriminant validity holds
Performance	<-->	AbsCapacity	0.89	Discriminant validity holds
Inbound	<-->	AbsCapacity	0.81	Discriminant validity holds

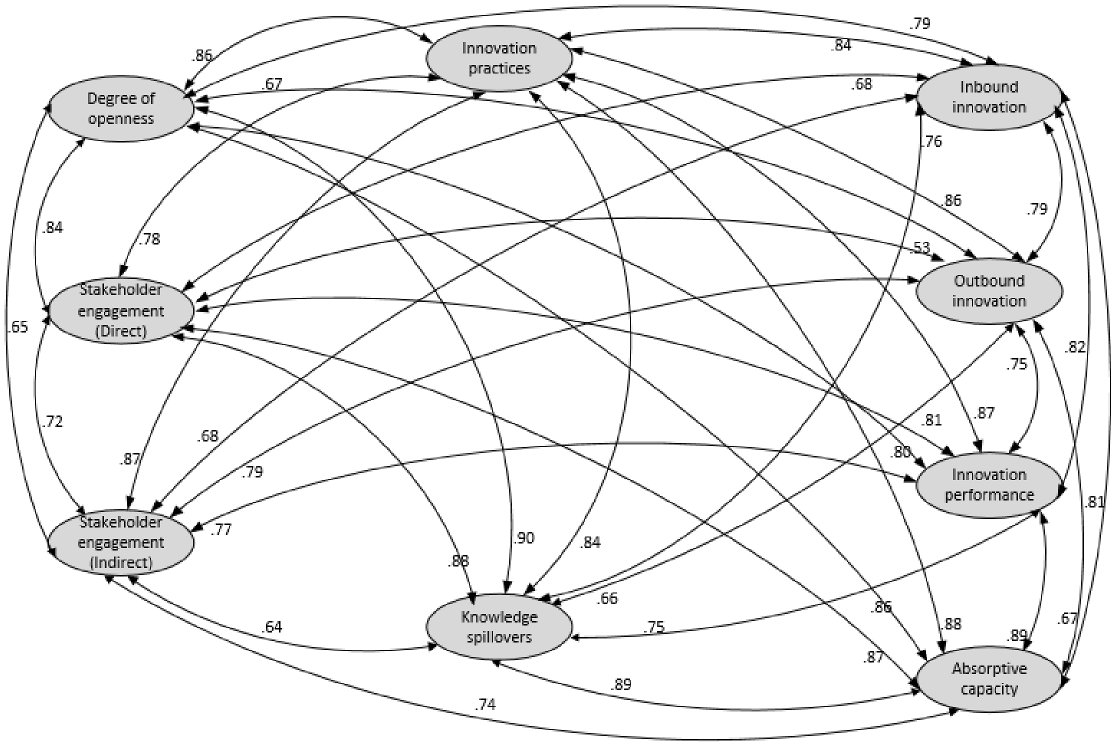

Figure 6.21: Final Full CFA Measurement Model (Respecified)

Table 6.39 Goodness of Fit Statistics for the Proposed Full CFA Measurement Model (Re-estimated)

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X²	4557.872 (0.00)	RMSEA	0.04	CFI	0.90	PCFI	0.74
DF	2100	RMR	0.06	IFI	0.90	PNFI	0.81
X²/df	2.170	SRMR	0.05	TLI	0.89	Pclose	1.00

Figure 6.21 presents the respecified model. The model fit statistics in Table 6.39 indicate that the full CFA model is admissible. The discriminant validity is re-estimated and the results are presented in Tables 6.40 and 6.41. The results in Table 6.40 suggest that no construct-to-construct correlation is above 0.90. As per Segar's (1997) suggestion, the chi-square difference test was conducted to check whether the chi-square difference between the constructs is significant. The results in Table 6.41 indicate that the chi-square difference is significant and the constructs presented in the full CFA measurement model are indeed unique.

Table 6.40: Discriminant Validity for the Final Full Measurement Model

Correlations			Estimate	Result (Method 1)
Openness	<-->	Indirect STK	0.65	Discriminant validity holds
Openness	<-->	Direct STK	0.84	Discriminant validity holds
Openness	<-->	Practices	0.86	Discriminant validity holds
Openness	<-->	KSP	0.90	Discriminant validity holds
Openness	<-->	Outbound	0.67	Discriminant validity holds
Openness	<-->	Performance	0.80	Discriminant validity holds
Openness	<-->	Inbound	0.79	Discriminant validity holds
Openness	<-->	Absorptive Capacity	0.86	Discriminant validity holds
Indirect STK	<-->	Direct STK	0.72	Discriminant validity holds
Indirect STK	<-->	Practices	0.87	Discriminant validity holds
Indirect STK	<-->	KSP	0.64	Discriminant validity holds
Indirect STK	<-->	Outbound	0.79	Discriminant validity holds
Indirect STK	<-->	Performance	0.77	Discriminant validity holds
Indirect STK	<-->	Inbound	0.68	Discriminant validity holds
Indirect STK	<-->	Absorptive Capacity	0.74	Discriminant validity holds
Direct STK	<-->	Practices	0.78	Discriminant validity holds
Direct STK	<-->	KSP	0.88	Discriminant validity holds
Direct STK	<-->	Outbound	0.53	Discriminant validity holds
Direct STK	<-->	Performance	0.81	Discriminant validity holds
Direct STK	<-->	Inbound	0.68	Discriminant validity holds
Direct STK	<-->	Absorptive Capacity	0.87	Discriminant validity holds
Practices	<-->	KSP	0.84	Discriminant validity holds
Practices	<-->	Outbound	0.86	Discriminant validity holds
Practices	<-->	Performance	0.87	Discriminant validity holds
Practices	<-->	Inbound	0.84	Discriminant validity holds
Practices	<-->	AbsCapacity	0.88	Discriminant validity holds
KSP	<-->	Outbound	0.66	Discriminant validity holds
KSP	<-->	Performance	0.77	Discriminant validity holds
KSP	<-->	Inbound	0.76	Discriminant validity holds
KSP	<-->	AbsCapacity	0.89	Discriminant validity holds
Outbound	<-->	Performance	0.75	Discriminant validity holds
Outbound	<-->	Inbound	0.79	Discriminant validity holds
Outbound	<-->	AbsCapacity	0.67	Discriminant validity holds
Performance	<-->	Inbound	0.82	Discriminant validity holds
Performance	<-->	AbsCapacity	0.89	Discriminant validity holds
Inbound	<-->	AbsCapacity	0.81	Discriminant validity holds

Table 6. 41 Discriminant Validity of the Final CFA Full Measurement Model (Method 2)

Construct		CR	AVE	Degree of Openness			Direct stakeholders			Indirect stakeholders			Innovation practices			Knowledge spillovers			Inbound innovation			Outbound innovation			Innovation performance			Absorptive capacity		
				X^2	Df	P	X^2	Df	P	X^2	Df	P	X^2	Df	P	X^2	Df	P	X^2	Df	P	X^2	Df	P	X^2	Df	P	X^2	Df	P
Degree of Openness	Correlation set free						779.868	105	0.000	538.171	81	0.000	1157.9	162	0.000	870.752	105	0.000	838.223	81	0.000	835.977	132	0.000	877.726	105	0.000	966.62	132	0.000
	Correlation						273.539	102	0.000	240.076	78	0.000	495.668	159	0.000	210.369	102	0.000	364.379	78	0.000	509.125	129	0.000	368.421	102	0.000	349.34	129	0.000
	Difference	0.90	0.60				506.329	3		298.095	3		662.23	3		660.383	3		473.844	3		326.852	3		509.305	3		617.27	3	
Direct stakeholders	Correlation set free			779.868	105	0.000				510.492	42	0.000	664.577	105	0.000	658.86	60	0.000	527.134	42	0.000	520.364	81	0.000	739.471	60	0.000	794.64	81	0.000
	Correlation			273.539	102	0.000				142.3	39	0.000	196.578	102	0.000	88.225	57	0.005	230.676		0.000	338.073	78	0.000	234.352	57	0.000	185.3	78	0.000
	Difference	0.87	0.62	506.329	3					368.192	3		570.635	3		570.635	3		296.458	42		182.291	3		505.119	3		609.35	3	
Indirect stakeholders	Correlation set free			538.171	81	0.000	510.492	42	0.000				844.24	81	0.000	334.891	42	0.000	360.009	27	0.000	924.448	105	0.000	560.371	42	0.000	511.36	60	0.000
	Correlation			240.076	78	0.000	142.3	39	0.000				159.181	78	0.000	64.541	39	0.000	43.539	24	0.009	380.678	102	0.000	102.001	39	0.000	83.389	57	.013
	Difference	0.90	0.74	298.095	3		368.192	3					685.059	3		270.35	3		316.47	3		543.77	3		458.37	3		427.97	3	
Innovation practices	Correlation set free			1157.9	162	0.000	664.577	105	0.000	844.24	81	0.000				813.893	105	0.000	750.705	81	0.000	1094.58	132	0.000	962.745	105	0.000	959.39	132	0.000
	Correlation			495.668	159	0.000	196.578	102	0.000	159.181	78	0.000				219.29	102	0.000	190.597	78	0.000	422.07	129	0.000	268.285	102	0.000	234.49	129	0.000
	Difference	0.91	0.64	662.23	3		685.059	3		685.059	3					594.603	3		560.108	3		672.51	3		694.46	3		724.9	3	
Knowledge spillovers	Correlation set free			870.752	105	0.000	658.86	60	0.000	334.891	42	0.000	813.893	105	0.000				564.278	42	0.000	912.599	132	0.000	570.434	60	0.000	851.4	81	0.000
	Correlation			210.369	102	0.000	88.225	57	0.005	64.541	39	0.000	219.29	102	0.000				167.417	39	0.000	515.877	129	0.000	146.874	57	0.000	180.09	78	0.000
	Difference	0.86	0.61	660.383	3		570.635	3		270.35	3		594.603	3					396.861	3		396.722	3		423.56	3		671.32	3	
Inbound innovation	Correlation set free			838.223	81	0.000	527.134	42	0.000	360.009	27	0.000	750.705	81	0.000	564.278	42	0.000				712.255	60	0.000	651.453	42	0.000	702.91	60	0.000
	Correlation			364.379	78	0.000	230.676		0.000	43.539	24	0.009	190.597	78	0.000	167.417	39	0.000				235.968	57	0.000	149.799	39	0.000	187.71	57	0.000
	Difference	0.85	0.65	473.844	3		296.458	42		316.47	3		560.108	3		396.861	3					476.287	3		501.654	3		515.2	3	
Outbound innovation	Correlation set free			835.977	132	0.000	520.364	81	0.000	924.448	105	0.000	1480.56	195	0.000	1094.58	132	0.000	712.255	60	0.000				761.189	81	0.000	657.03	105	0.000
	Correlation			509.125	129	0.000	338.073	78	0.000	380.678	102	0.000	672.455	192	0.000	422.07	129	0.000	235.968	57	0.000				330.208	78	0.000	320.1	102	0.000
	Difference	0.90	0.66	326.852	3		182.291	3		543.77	3		808.1	3		672.51	3		476.287	3					430.981	3		336.93	3	
Innovation performance	Correlation set free			877.726	105	0.000	739.471	60	0.000	560.371	42	0.000	962.745	105	0.000	570.434	60	0.000	651.453	42	0.000	761.189	81	0.000				940.28	81	0.000
	Correlation			368.421	102	0.000	234.352	57	0.000	102.001	39	0.000	268.285	102	0.000	146.874	57	0.000	149.799	39	0.000	330.208	78	0.000				202.11	78	0.000
	Difference	0.90	0.71	509.305	3		505.119	3		458.37	3		694.46	3		423.56	3		501.654	3		430.981	3					738.17	3	
Absorptive capacity	Correlation set free			966.617	132	0.000	794.644	81	0.000	511.358	60	0.000	959.385	132	0.000	851.403	81	0.000	702.907	60	0.000	657.029	105	0.000	940.279	81	0.000			
	Correlation			349.343	129	0.000	185.297	78	0.000	83.389	57	0.013	234.489	129	0.000	180.088	78	0.000	187.707	57	0.000	320.095	102	0.000	202.108	78	0.000			
	Difference	0.92	0.70	617.274	3		609.347	3		427.969	3		724.896	3		671.315	3		515.2	3		336.934	3		738.171	3				

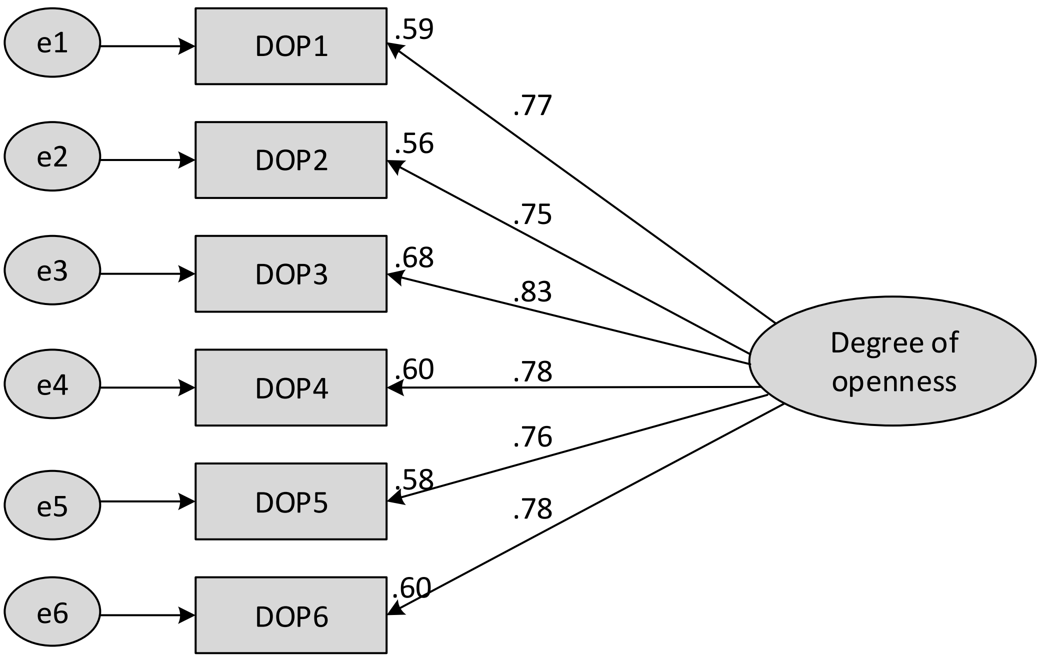

Figure 6.22: Re-estimated Degree of Openness Measurement Model

Figure 6.22 presents the re-estimated model for the degree of openness. The results suggest that the degree of openness construct shows acceptable model fit after the item DOP7 was deleted (see Table 6.42). Table 6.42 presents statistics for the re-estimated degree of openness measurement model.

Table 6.42: Statistics for Re-estimated Degree of Openness Measurement Model

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	79.364(0.00)	RMSEA	0.05	CFI	0.98	PCFI	0.59
DF	27	RMR	0.03	IFI	0.98	PNFI	0.58
X^2/df	2.939	SRMR	0.05	TLI	0.96	Pclose	0.33
Factor loadings (P < 0.001***, P < 0.01**, P < 0.05*)							
Item	SE		CR	P	SMC	Comment	
DOP1	0.77		11.271	***	0.59	Model is identified	
DOP2	0.75		9.979	***	0.56		
DOP3	0.83		10.914	***	0.68		
DOP4	0.78		11.033	***	0.60		
DOP5	0.76		10.905	***	0.58		
DOP6	0.78		11.030	***	0.60		
DOP7	Deleted						
Model fit is admissible							

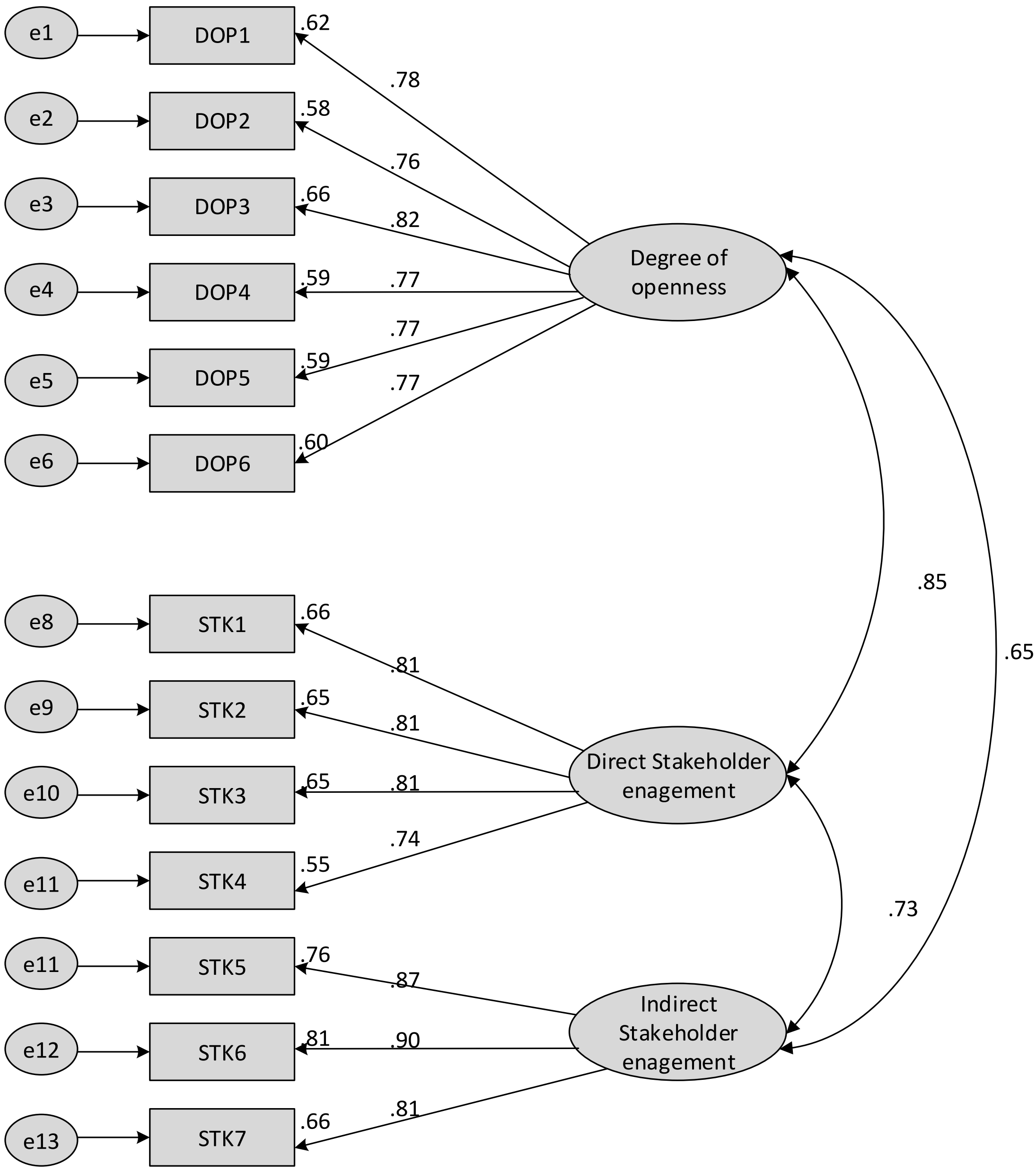

Figure 6.23: Full Measurement model for Technical Inputs Constructs (Re-estimated)

Table 6.43 Goodness of Fit Statistics and Validity Measures for Technical Inputs

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	567.887(0.00)	RMSEA	0.05	CFI	0.94	PCFI	0.75
DF	186	RMR	0.06	IFI	0.94	PNFI	0.72
X^2/df	3.05	SRMR	0.05	TLI	0.92	Pclose	0.07

Factor loadings
($P < 0.001$***, $P < 0.01$**, $P < 0.05$*)

Factor	CR	AVE	Item	SFL	SMC	Comment
			DOP1	0.78	0.60	
DOP	0.90	0.60	DOP2	0.76	0.59	
			DOP3	0.82	0.65	
			DOP4	0.77	0.59	
			DOP5	077	0.60	
			DOP6	0.77	0.60	
			Deleted			
			STK1	0.81	0.66	
Direct STK	0.87	0.63	STK2	0.81	0.65	
			STK3	0.81	0.66	
			STK4	0.74	0.55	
			STK5	0.87	0.76	
Indirect STK	0.90	0.74	STK6	0.90	0.81	
			STK7	0.81	0.66	
Model fit acceptable						

Figure 6.23 presents the re-estimated full measurement model for technical input constructs. The results suggest an acceptable fit (see Table 6.43). Hence, the full CFA measurement model is accepted for use in structural modelling.

6.6 Final Reliability

On examining the measurement models underlying the research constructs presented earlier, the instrument is checked for reliability prior to developing the structural models. Reliability assesses the trustworthiness of the measurement instrument. Bryman and Bell (2011) suggest that the most commonly used method for measuring internal consistency is Cronbach's α, as it calculates the average of all possible reliability coefficients. The alpha coefficient 0 indicates no internal reliability and 1 indicates perfect internal reliability. Values above 0.70 should be considered a rule of thumb sufficient for internal consistency (Bryman & Bell 2011; Hair et al. 2010). Table 6.44 presents the reliability estimates for each construct. Cronbach's alpha values are all above the 0.7 threshold, suggesting that the instrument is reliable.

Table 6.44: Instrument Reliability

Construct	No. of items	Cronbach's alpha
Degree of openness	6	0.90
Stakeholder engagement (direct)	4	0.87
Stakeholder engagement (indirect)	3	0.90
Innovation practices	6	0.91
Knowledge spill-overs	4	0.86
Inbound innovation	3	0.84
Outbound innovation	5	0.91
Innovation performance	4	0.90
Absorptive capacity	5	0.92
Total	39	

6.7 Summary

The goal of this chapter was to present the approaches adopted for validating the research instrument. Section 6.2 presented a summary of steps adopted to establish content validity. Section 6.3 detailed the steps involved in purifying the initial measure. Section 6.4 focussed on establishing the dimensionality with EFA. Section 6.5 explained the process used for construct validity with convergent validity and discriminant validity. Based on the results, the final CFA measurement model was specified in Section 6.5.8. Section 6.6 presented the average of all possible reliability coefficients to indicate the trustworthiness of the measurement instrument. The full measurement model presented in Figure 6.19 will be used in the following chapter to design the structural model and to test the research hypotheses.

Chapter 7: Research Findings and Discussion

7.1 Introduction

The objective of this chapter is to present and discuss the key findings of this study. This chapter presents the results of the data analysis conducted earlier. The research questions presented in Chapter 1 will be addressed by analysing the results of the data analysis. This study argues that organisations within a close proximity are ahead in terms of OI and achieve higher innovation performance. This study also investigates the mediating role of AC and antecedent factors in achieving OI and innovation performance. Built on this argument, a research model was developed and presented in Chapter 3. This chapter is organised into eight sections. Section 7.2 provides an overview of the extent of constructs presented in the research model. Section 7.3 presents the structural model. Section 7.4 illustrates the multi-group analysis to indicate the differences between the two groups selected for this study. Section 7.5 outlines the non-parametric (Kruskal-Wallis) test results for all the constructs. Section 7.6 revisits the research model and tests the hypotheses. Section 7.7 presents a discussion and details the findings. Section 7.8 summarises the content of this chapter.

7.2 Descriptive Findings

This section presents an overview of the impact of technical inputs and business models on OI and economic outputs, which include inbound innovation, outbound innovation and innovation performance. GOF statistics for the measurement model are presented in Chapter 6. The measurement model presented in Section 7.3 is the basis for the descriptive analysis of OI and its antecedent factors.

7.2.1 Overview of Open Innovation-based Constructs for Innovation Performance

The aim of this section is to evaluate the extent of the OI-based constructs among Indian IT organisations within and outside the IT cluster. Chapter 4 presented the variables developed to measure the OI constructs, AC and innovation performance. A 5-point

Likert scale (1: ‘Strongly disagree’, 2: ‘Disagree’, 3: ‘Neither agree nor disagree’, 4: ‘Agree’, 5: ‘Strongly Agree’) was used to measure responses. Figure 7.1 presents an overview of the extent of the OI-based constructs among Indian IT organisations.

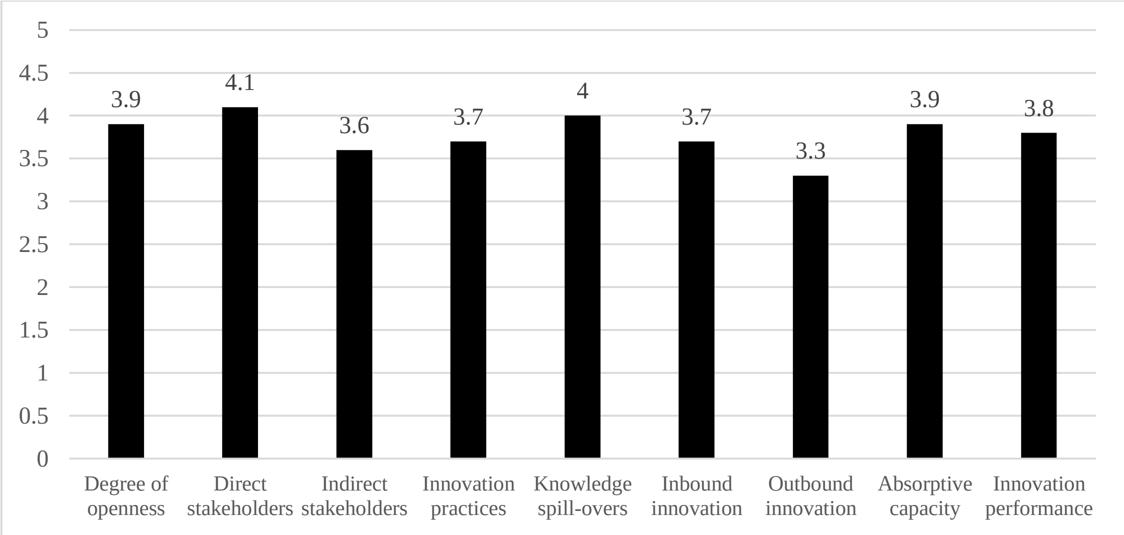

Figure 7.1: Overview of constructs among Indian IT Organisations

The results indicate that all constructs received above the scale medians. Overall, the highest average mean scores are from the constructs direct stakeholder engagement and knowledge spill-overs. The outbound innovation construct received marginally lower scores compared to inbound innovation. The mean scores for the other OI-related constructs degree of openness, indirect stakeholder engagement, innovation practices received less than 4. To investigate the role of clustering on OI constructs, AC capacity and innovation performance, the mean scores of IT organisations within the IT cluster are compared against the IT organisations outside the IT cluster. Figure 7.2 below shows the effect of clustering on the constructs.

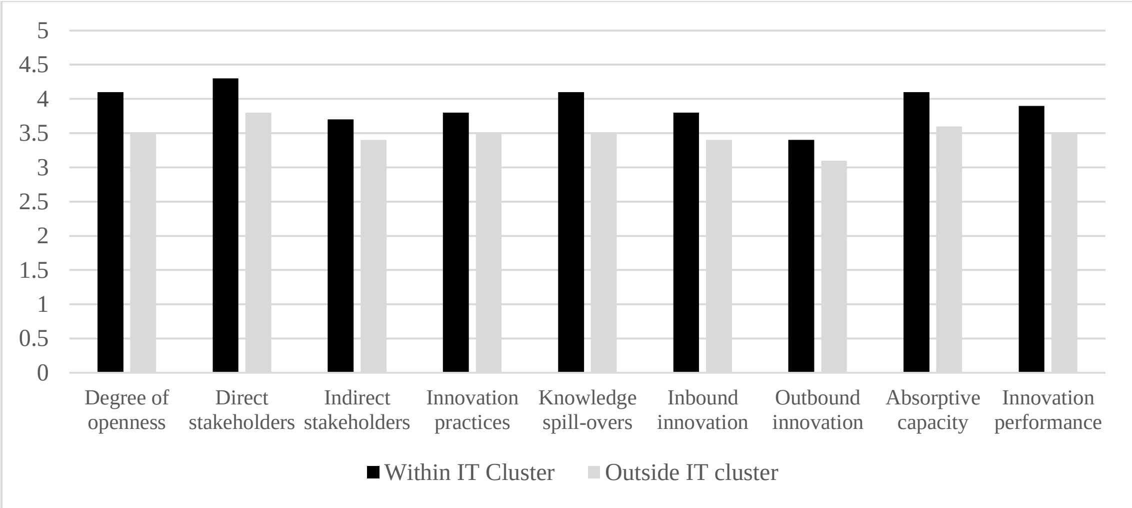

Figure 7.2: The Effect of Clustering on Constructs among Indian IT Organisations

The results illustrate the difference in the mean scores of IT organisations within and outside the IT cluster. Overall, organisations within the IT cluster achieved higher mean scores compared to the organisations outside the IT cluster. Except for outbound innovation, all constructs received higher than 3.5 as a mean score. Organisations outside the IT cluster achieved scores higher than 3 but lower than the other group.

Table 7.1: Independent Sample t-test on Organisation Location

Construct	Mean	t	p	Mean difference	Std. error
Degree of openness	3.8	4.78	0.00	0.54	0.11
Direct stakeholder engagement	4	4.42	0.00	0.47	0.10
Indirect stakeholder engagement	3.5	1.74	0.09	0.23	0.13
Innovation practices	3.6	2.96	0.02	0.35	0.12
Knowledge spill-overs	3.8	5.55	0.00	0.59	0.10
Inbound innovation	3.6	2.79	0.01	0.34	0.12
Outbound innovation	3.2	2.05	0.08	0.29	0.14
Absorptive capacity	3.8	4.34	0.00	0.46	0.10
Innovation performance	3.7	3.37	0.00	0.38	0.11

The independent sample t-test in Table 7.1 suggests that the mean differences for the all constructs except indirect stakeholder engagement and outbound innovation are statistically significant ($p < 0.05$). A possible explanation is that organisations within the IT cluster have better opportunities for interaction and knowledge sharing. As the effect of clustering was noticeable, further analysis was conducted to examine the impact of organisation size. The responses were divided into large and small- and medium-sized (SME) organisations, with organisations with fewer than 200 employees considered SMEs. Figure 7.3 shows the effect of organisation size on the constructs.

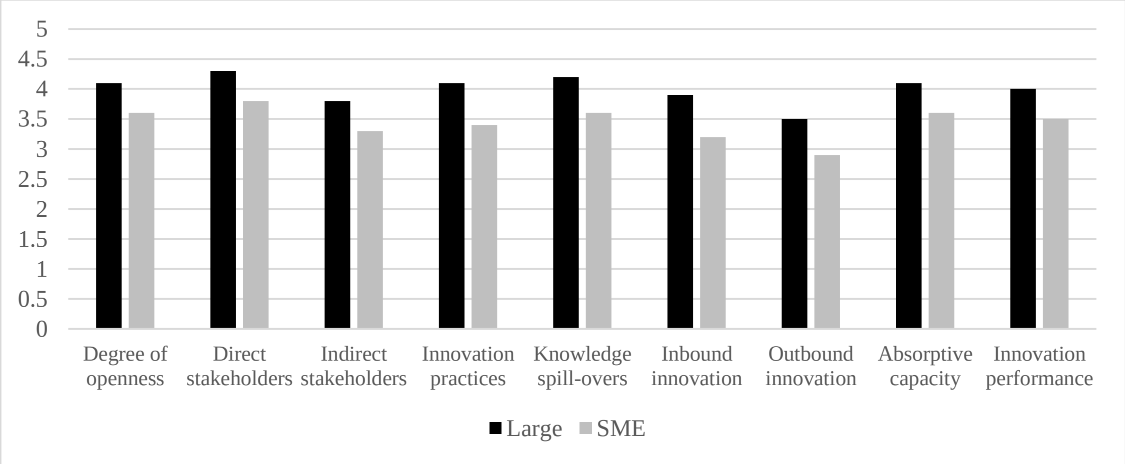

Figure 7.3: Effect of Organisation Size

The large organisations achieved higher mean scores than the smaller organisations (see Figure 7.3). The large organisations achieved 3.5 or higher as mean scores, whereas smaller organisations received lower than 3.5 mean scores except for degree of openness, direct stakeholder engagement, knowledge spill-overs and AC.

Table 7.2: Independent Sample t-test on Organisation Size

Construct	Mean	t	p	Mean difference	Std. error
Degree of openness	3.8	5.24	0.00	0.55	0.10
Direct stakeholder engagement	4	4.49	0.00	0.45	0.10
Indirect stakeholder engagement	3.5	3.77	0.00	0.47	0.12
Innovation practices	3.6	4.91	0.00	0.54	0.11
Knowledge spill-overs	3.8	5.65	0.00	0.56	0.10
Inbound innovation	3.6	6.39	0.00	0.72	0.11
Outbound innovation	3.2	4.95	0.00	0.64	0.13
Absorptive capacity	3.8	5.46	0.00	0.53	0.09
Innovation performance	3.7	5.49	0.00	0.57	0.10

The independent sample t-test on organisation size suggests that the mean differences between large organisations and SMEs are highly significant ($p < 0.05$) (see Table 7.2). A possible explanation is that the large organisations have access to a range of resources and skills compared with SMEs. As a result, the large organisations tend to participate more in OI activities. The following sections examine each of the constructs separately with their indicators.

Degree of Openness

The extent to which Indian IT organisations show openness is shown in Figure 7.4.

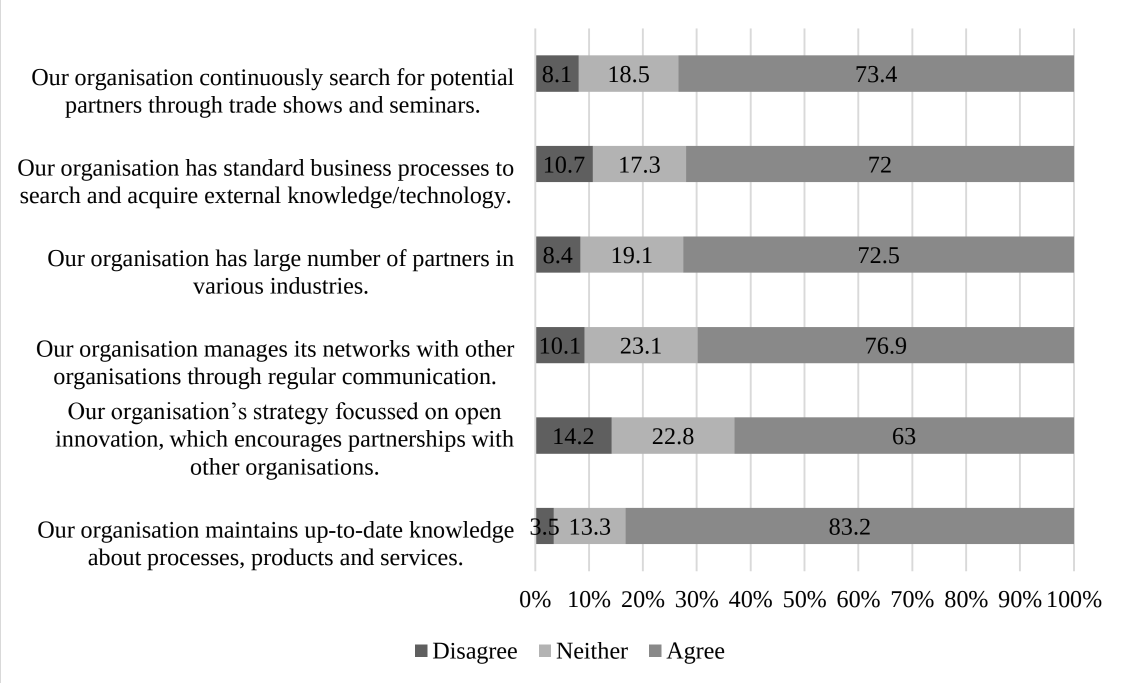

Figure 7.4: Degree of Openness

Degree of openness is an organisation's willingness to cooperate with other firms. It involves ensuring appropriate practices for searching for new partners to acquire new knowledge. More than 83% of organisations in the survey maintain up-to-date knowledge about processes, products and services (see Figure 7.4). A total of 63% of respondents indicated that their organisation has a strategy to encourage partnerships with other organisations. Further, 72% of organisations have business processes to search for and acquire external knowledge. These results are further strengthened by the organisations' willingness to search for new partners and acquire external knowledge. A total of 73.4% of respondents indicated that their organisation continuously searches for new partners through trade shows and seminars. Some 72.5% of respondents also believe that their organisation has partners in various industries and 76.9% indicated that their organisation communicates and manages their networks.

Stakeholder Engagement (Direct)

Stakeholders are individuals who play an important role in an organisation's OI efforts. To gain an insight into the importance of stakeholders in OI projects, they are divided into direct and indirect stakeholders. The importance of direct stakeholders is reflected in Figure 7.5.

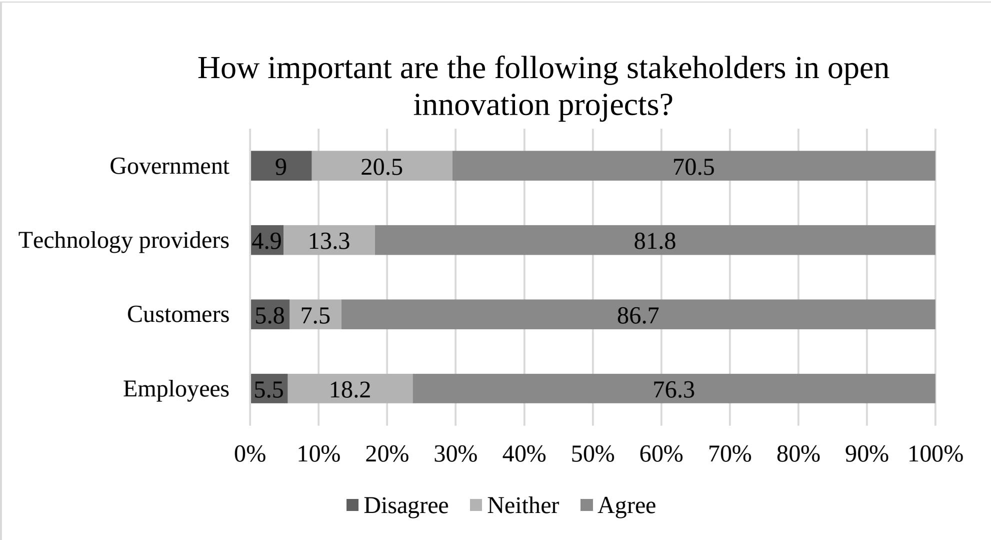

Figure 7.5: Direct Stakeholders

A total of 70.5% of respondents consider the government an important stakeholder in OI projects, while 81.8% agree that the technology providers are important. Some 76.3% of respondents indicated that employees are the most important stakeholders. With regards to customers, 86.7% of respondents view these as the most important stakeholders compared with the other stakeholders.

Stakeholder Engagement (Indirect)

The importance of indirect stakeholders in OI projects is presented in Figure 7.6.

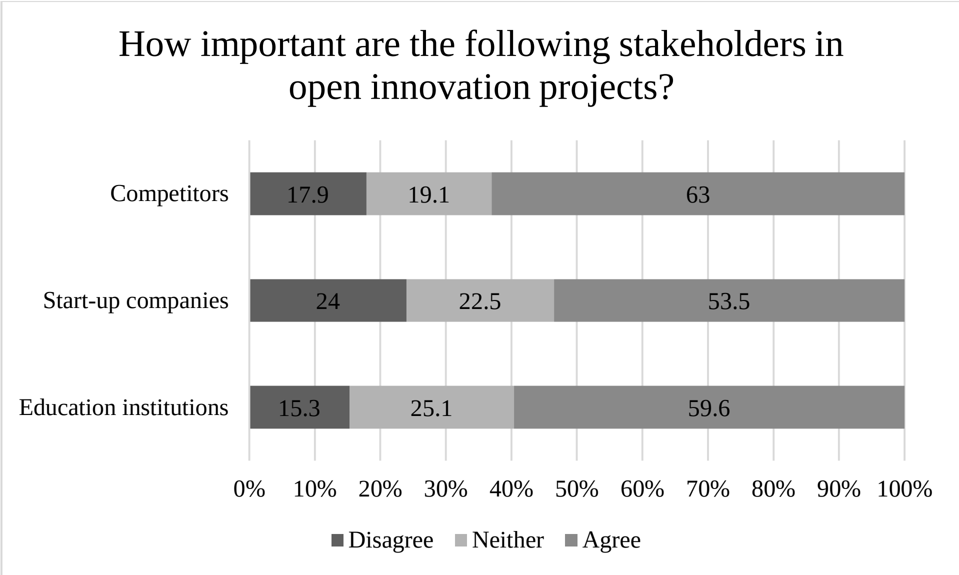

Figure 7.6: Indirect Stakeholders

Education institutions, start-up companies and competitors are categorised as indirect stakeholders as their interests are either enhanced or threatened. The survey results indicate that both education institutions ((59.6% of respondents) and start-up companies (53.5% of respondents) play an important role in OI projects. However, 63% of survey respondents indicated that competitors are more important indirect stakeholders than the other two indirect stakeholders.

Innovation Practices

The extent to which Indian IT organisations allow their employees to participate in R&D activities is shown in Figure 7.7.

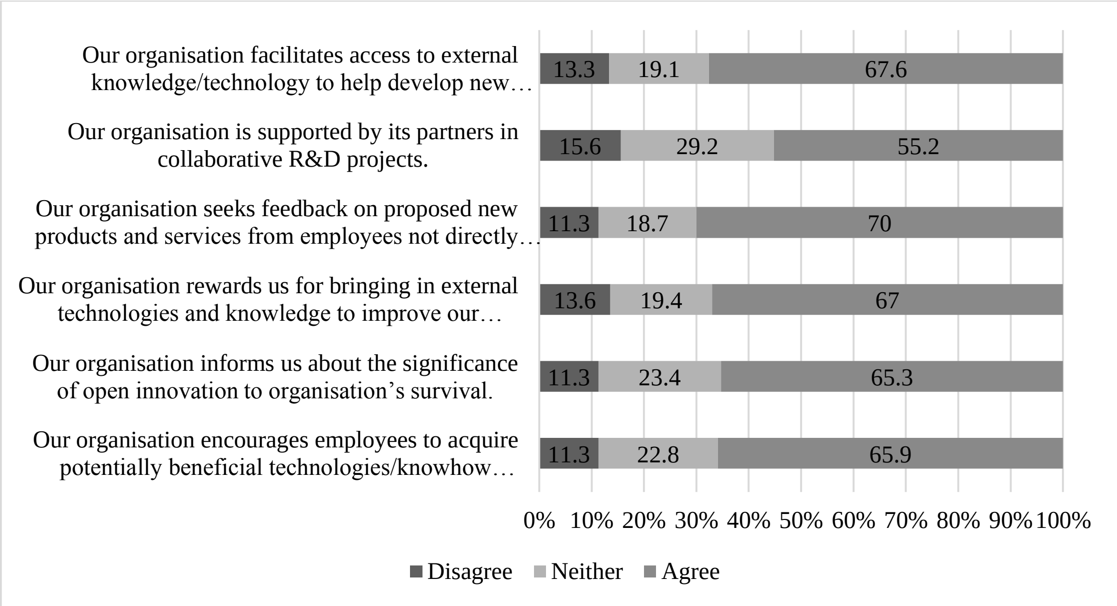

Figure 7.7: Innovation Practices

Innovation practices are characterised by organisation efforts to adopt appropriate practices and a reward system to encourage collaboration and knowledge exchange. The results suggest that more than 67% of organisations in the survey allow their employees to access external knowledge and technology (see Figure 7.7). However, only 55.2% of organisations are supported by their partners in R&D projects. Interestingly, 65.3% organisations informed their employees about the importance of OI to the organisation's survival—in fact, 65.9% organisations encouraged their employees to acquire external knowledge from external sources and 67% organisations rewarded their employees for utilising external knowledge and technologies to improve products and services.

Knowledge Spill-overs

Figure 7.8 provides an overview of knowledge flows among IT organisations.

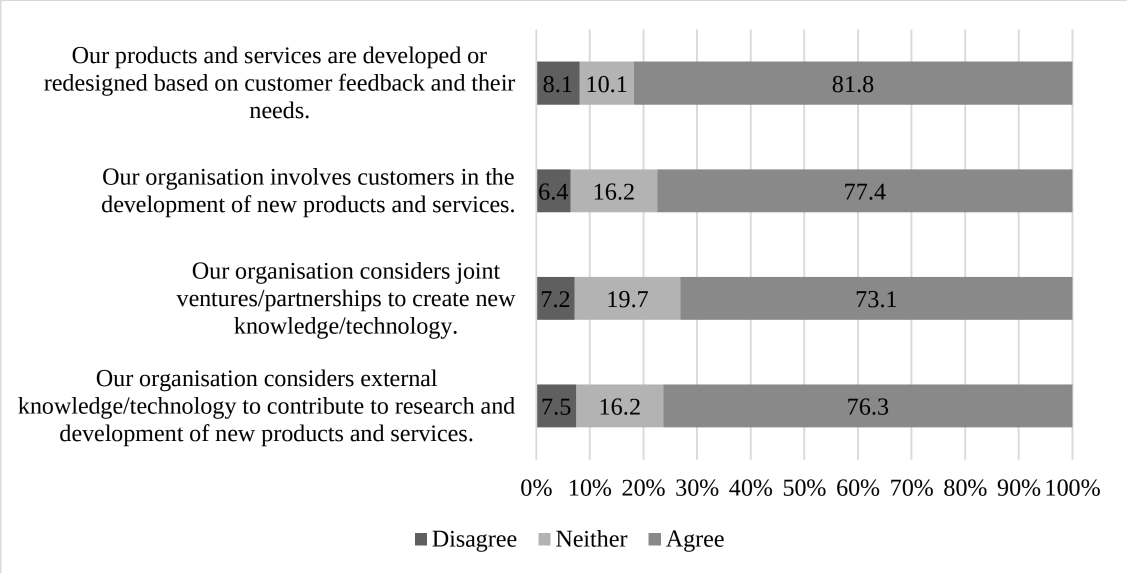

Figure 7.8: Knowledge Spill-overs

Knowledge capital can be transported across organisational boundaries easily without tariffs. In the OI context, knowledge spill-overs are considered potential resources for innovation. A total of 76.3% of respondents agree that their organisation considers external knowledge in developing new products and services, while 81.8% indicated that their organisations develops new products and services using customer feedback. 77.4% of organisations had gone one step further and involved customers in the development process. Interestingly, 73.1% of respondents indicated that their organisation considers partnerships to create new knowledge and technology.

Inbound Innovation

IT organisations' inbound innovation efforts are presented in Figure 7.9. OI efforts involve facilitation of knowledge flows both inward (inbound) and outward (outbound). The results indicate that 74.8% of organisations upgrade existing technology to stay ahead of their competitors, while 54.9% of respondents indicated that their organisation is willing to buy intellectual property rights from other organisations. In fact, 58.4% of respondents specified that their organisation bought intellectual property rights from others to develop new products and services.

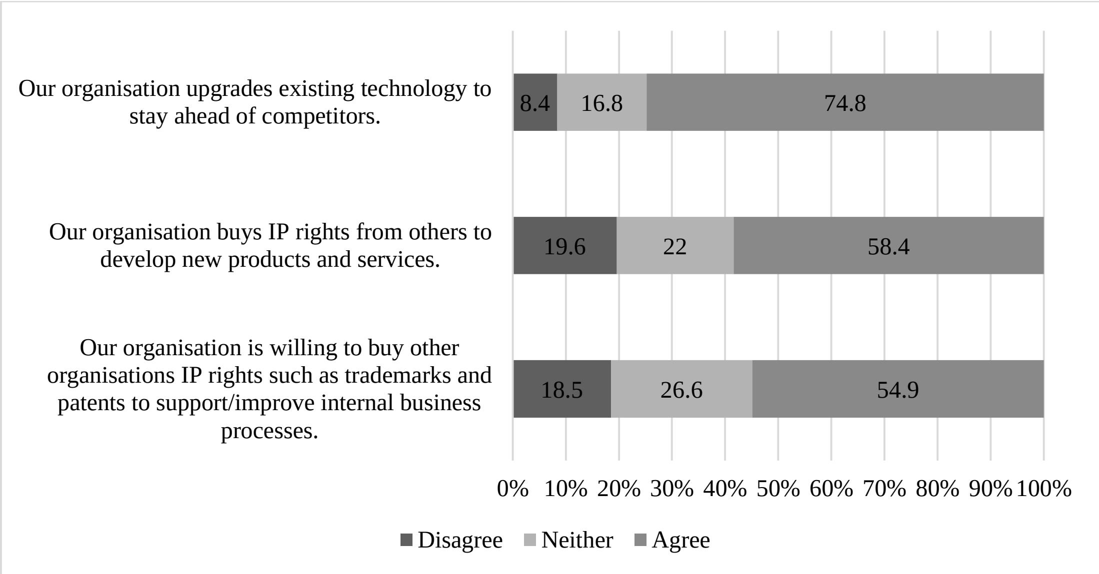

Figure 7.9: Inbound Innovation

Outbound Innovation

Organisation efforts to share and commercialise knowledge are shown in Figure 7.10.

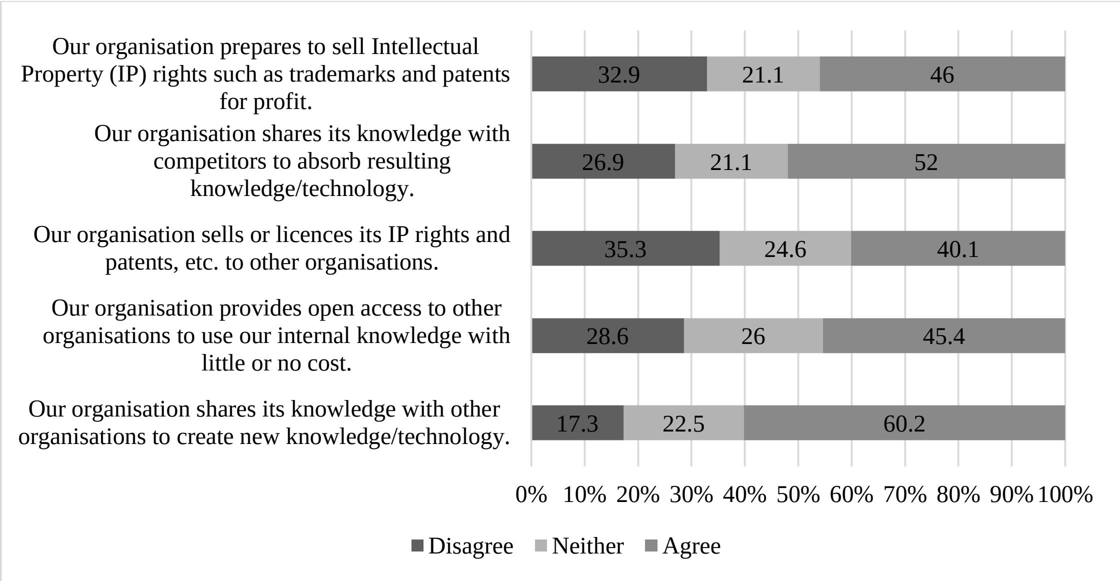

Figure 7.10: Outbound Innovation

Outbound innovation activities include sharing knowledge with others and commercialising intellectual property rights. Only 45.4% respondents agreed that their organisation provides open access to other organisations to use their knowledge at little or no cost. Only 52% of respondents indicated that their organisation shares knowledge with competitors to absorb resulting knowledge and technology. Interestingly, 60.2% of respondents specified that their organisation shares knowledge with others to create new knowledge and technology. With regards to commercialising internal innovations, 46% of respondents indicated that their organisation is prepared to sell intellectual property rights, while only 40.1% of respondents specified that their organisation sells IP rights to other organisations.

Absorptive Capacity

The role of AC in improving innovation performance is shown in Figure 7.11.

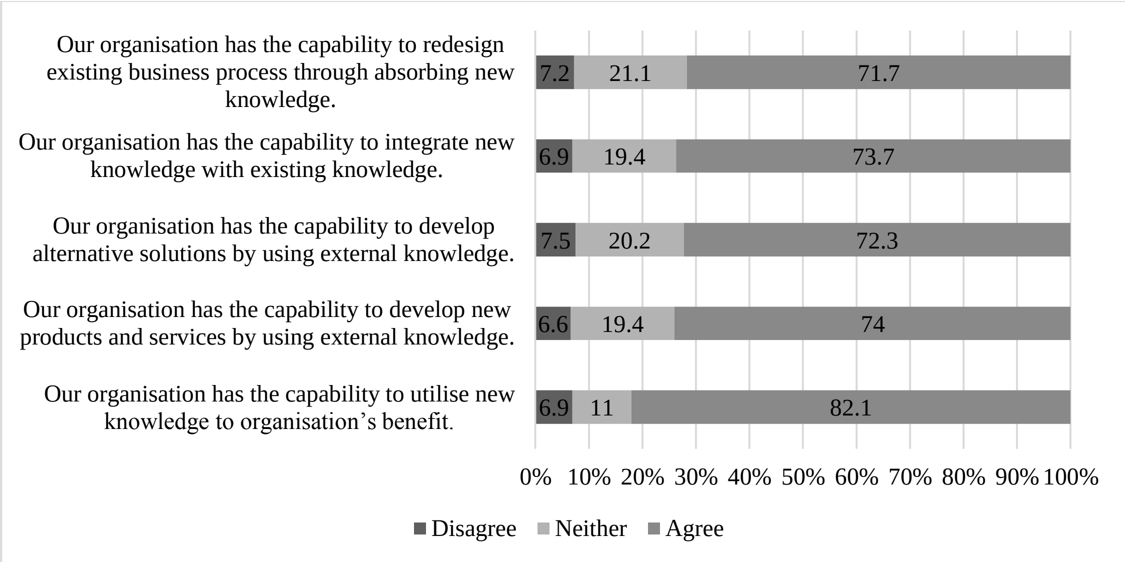

Figure 7.11: Absorptive Capacity

The organisation's ability to absorb and apply external knowledge mediates innovation performance. The majority of respondents (82.1%) indicated that their organisation has the capability to utilise new knowledge for the organisation's benefit. With regards to making use of the absorbed knowledge, 73.7% of respondents believe that their organisation can integrate external knowledge with internal knowledge, while 71.7% of respondents specified that their organisations have the capability to redesign business processes through absorbed knowledge. However, 74% of respondents are of the view that their organisation has the capability to develop new products and services with the absorbed knowledge.

Innovation Performance

The level of innovation performance of IT organisations over the last three years is shown in Figure 7.12.

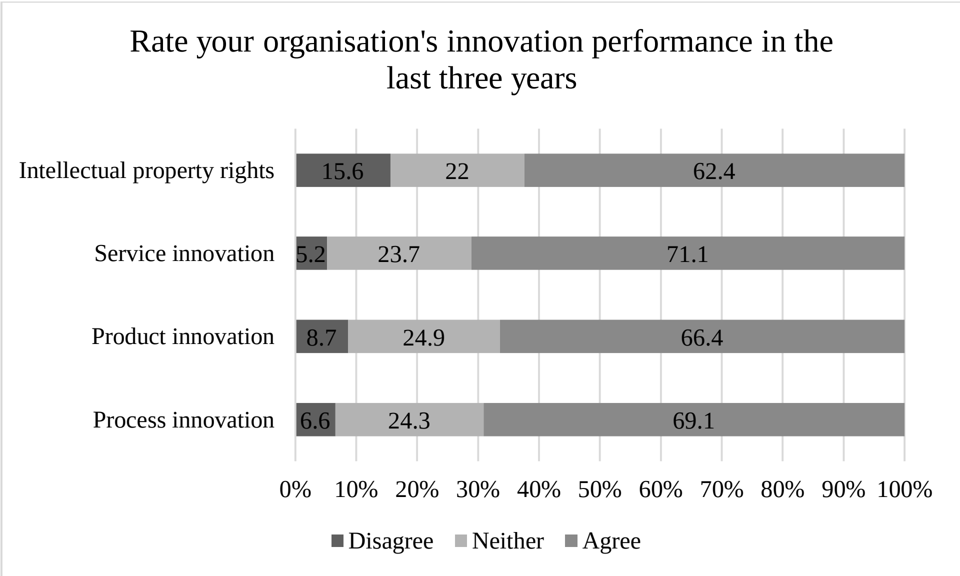

Figure 7.12: Innovation Performance

Innovation performance is the result of inbound and outbound innovation activities in IT organisations. 62.4% of respondents agreed that their organisation has improved in term of intellectual property rights, while 66.4% and 69.1% of respondents respectively specified that their organisation has seen improvements in product innovation and process innovations. The majority of respondents (71.1%) indicated that their organisation has seen improvements in services in the last three years.

7.3 Structural Model and Hypothesis Testing

This section utilises the measurement model to examine the relationships among constructs presented in the previous chapter. According to Hair et al. (2010), the structural model is a set of relationships among constructs based on the hypothesised model. The SEM technique is commonly used to develop and assess relationships among constructs. SEM is a multivariate technique, which combines both factor analysis and multiple regression techniques to represent the theory with a set of structural equations in the form of a visual diagram. Sections 7.3, 7.4 and 7.5 present the structural model results.

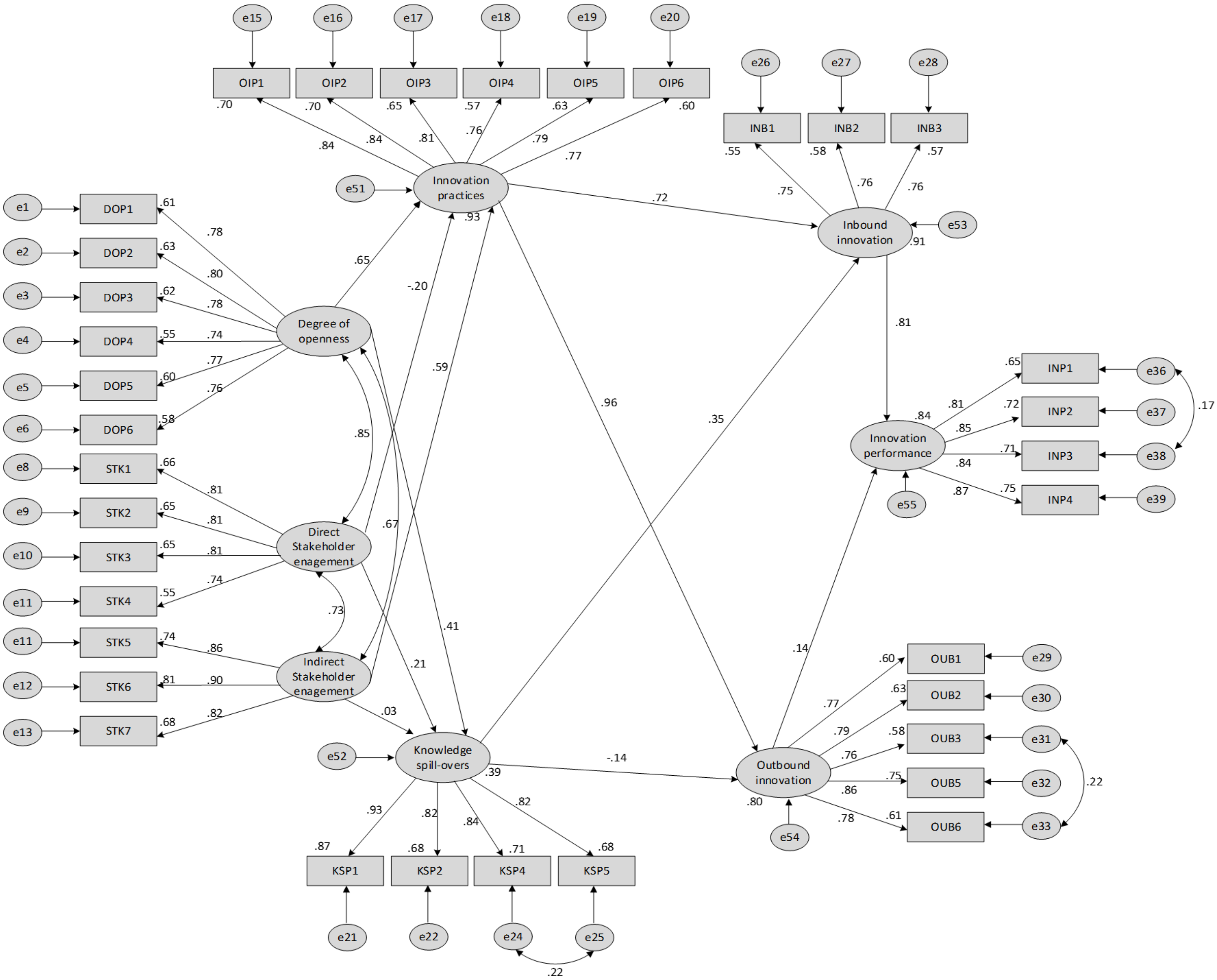

Figure 7.13a: The Structural Model

The structural model in Figure 7.13a includes 35 items. It has been evaluated for GOF, and the model fit statistics are presented in Table 7.3a.

Table 7.3a: Model Fit Statistics for Structural Model

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	4355.998(0.00)	RMSEA	0.05	CFI	0.90	PCFI	0.78
DF	1617	RMR	0.09	IFI	0.90	PNFI	0.73
X^2/df	2.69	SRMR	0.08	TLI	0.89	Pclose	0.65

The thresholds for the model fit indices (absolute, incremental and parsimony) were discussed in detail in Chapter 6 (see Tables 6.9 and 6.10). In summary, the acceptable normed chi-square value is below 5, but less than 3 is preferred. For the other absolute fit index (RMSEA, RMR and RMR) values, less than 0.08 is preferred with a threshold value of 0.10. The acceptable incremental fit index values are above 0.90, while the parsimony fit index (PNFI and PCFI) values should be greater than 0.5. A Pclose value greater than 0.05 indicates a good model fit.

The structural model's normed chi-square is within the acceptable range. The absolute fit index (RMSEA, RMR and SRMR) values are 0.05, 0.09 and 0.08 respectively. The CFI and IFI values are within the acceptable range, but the TLI value was very close to the recommended threshold value of 0.90. Although it is optimal to achieve values above 0.90, Hair et al. (2010) suggests using either CFI or TLI for studies with more than 250 samples. This study consists of 346 samples and the CFI value of 0.90 or above suggests model fit. In addition, the parsimony fit indices and Pclose values were checked to strengthen the validity of the model. The PCFI and PNFI values were above 0.5 and the Pclose value was 0.65. These results indicate that the presented structural model is acceptable.

The loading estimates of the structural model presented in Figure 7.13a were compared against the corresponding full measurement model (Figure 6.19). According to Hair et al. (2010), an acceptable structural model is expected to have similar loadings to that of the measurement model. Similarities in loading estimates between models indicate parameter stability. A comparison of loading estimates between the two models suggest that all loadings are within the limit of 0.05 except one standardised estimate. A further assessment was conducted to compare the two models. Hair et al. (2010) explain that a structural model consists of fewer paths than the full measurement model and hence cannot fit any better than the measurement model. In summary, the results indicate acceptable model fit.

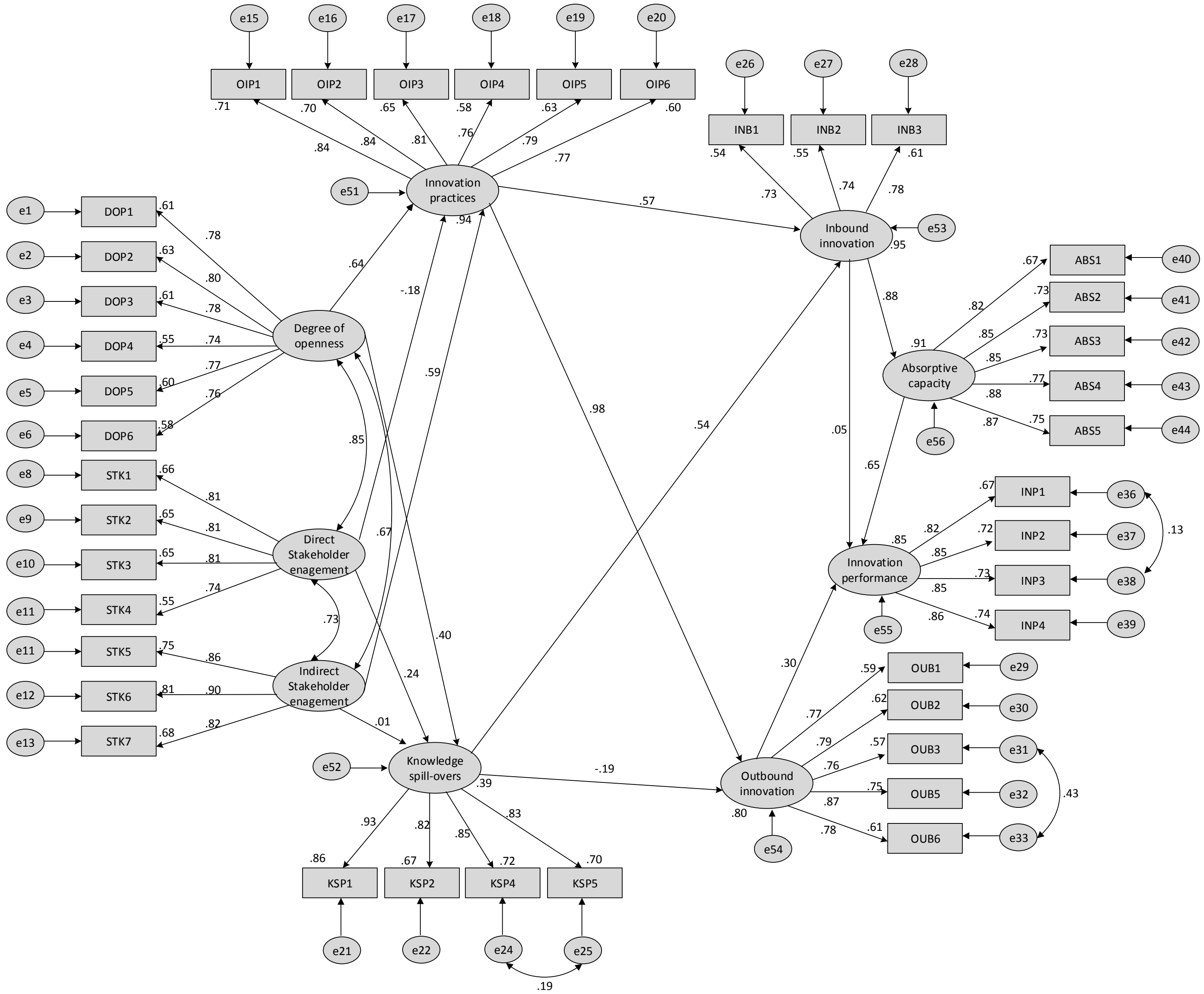

Figure 7.13b: The Structural Model with Absorptive Capacity

The structural model shown in Figure 7.13b includes AC with 40 items. It has been evaluated for GOF, with model fit statistics presented in Table 7.3b.

Table 7.3b: Model Fit Statistics for Structural Model with Absorptive Capacity

Chi-square		Absolute Fit Indices		Incremental Fit Indices		Parsimony Fit Indices	
X^2	5380.850(0.00)	RMSEA	0.04	CFI	0.90	PCFI	0.80
DF	2151	RMR	0.09	IFI	0.89	PNFI	0.73
X^2/df	2.50	SRMR	0.08	TLI	0.88	Pclose	1.00

The threshold for the model fit indices (absolute, incremental and parsimony) were discussed in detail in Chapter 6 (see Tables 6.9 and 6.10). In summary, the normed chi-square is within the acceptable range. The absolute fit index (RMSEA, RMR and SRMR) values are 0.04, 0.09 and 0.08 respectively. The CFI value is within the acceptable range, but the IFI and TLI values are very close to the recommended threshold value of 0.90. Although it is optimal to achieve values above 0.90, Hair et al. (2010) suggest using either CFI or TLI for studies with more than 250 samples. This study consists of 346 samples, so a CFI value of 0.90 or above suggests model fit. However, parsimony fit indices and Pclose values were also checked. The PCFI and PNFI values are above 0.5 range and the Pclose value is 1. These results indicate that the presented structural model is acceptable.

The loading estimates of the structural model presented in Figure 7.13b were compared against the corresponding full measurement model (see Figure 6.19). According to Hair et al. (2010), an acceptable structural model is expected to have similar loadings to that of the measurement model. Similarities in loading estimates between models indicate parameter stability. A comparison of loading estimates between the two models suggest that all loadings are within the limit of 0.05 except one standardised estimate. A further assessment was conducted to compare the two models.

The structural model consists of six dependent variables. To explain the extent of variance for the dependent variables (innovation practices, knowledge spill-overs, inbound innovation, outbound innovation, AC and innovation performance), the SMC was estimated (see Table 7.4).

Table 7.4: Variance Explained

Variance explained	SMC
Innovation practices	0.93
Knowledge spill-overs	0.39
Inbound innovation	0.91
Outbound innovation	0.80
Absorptive capacity	0.91
Innovation performance	0.84

Table 7.3a shows that the structural model explains 84% of the variance in innovation performance, 91% of the variance in AC (see Figure 7.3b), 80% of the variance in outbound innovation, 91% of the variance in inbound innovation, 39% of the variance in knowledge spill-overs and 93% of the variance in innovation practices. According to Hair et al. (2010), the goal of obtaining a specific total variance extracted by successive factors is to ensure practical significance. Although there are no absolute thresholds for cumulative percentages of total variance extracted, the values presented in Table 7.4 suggest relevance between the observed sample data and structural model. The 84% of variance in overall innovation performance supports the validity of the structural model.

The final evaluation of the measurement model was conducted to assess the strength of the paths within the model. Table 7.5 shows the strengths of the structural paths. Of the 13 theorised structural paths, 12 are significant at a 95% confidence interval. The results support the overall evaluation of the structural model is an acceptable representation of the sample data.

Table 7.5: Structural Paths of the Full Research Model

Path	Estimate	SE	CR	P
Degree of openness → Innovation practices	0.65	0.09	8.409	***
Stakeholder engagement (Direct) → Innovation practices	-0.19	0.08	-2.516	0.012
Stakeholder engagement (Indirect) → Innovation practices	0.59	0.04	10.905	***
Degree of openness → Knowledge spill-overs	0.40	0.18	4.372	***
Stakeholder engagement (Direct) → Knowledge spill-overs	0.24	0.16	2.065	0.03
Stakeholder engagement (Indirect) → Knowledge spill-overs	0.01	0.09	0.400	0.68
Innovation practices → Inbound innovation	0.56	0.07	9.775	***
Knowledge spill-overs → Inbound innovation	0.54	0.04	8.481	***
Knowledge spill-overs → Outbound innovation	-0.19	0.05	-1.716	0.08
Inbound innovation → Absorptive capacity	0.95	0.06	13.790	***
Innovation practices → Outbound innovation	0.98	0.08	12.156	***
Inbound innovation→ Innovation performance	0.81	0.09	7.827	***
Outbound innovation → Innovation performance	0.31	0.08	1.542	***
Absorptive capacity → Innovation performance	0.70	0.17	3.808	***

****Significant at 0.001*

7.4 Multi-group Analysis for Geographic Proximity

Multi-group analysis helps to test differences between different groups of survey respondents (Hair et al. 2010). The primary goal of analysing multiple groups is to understand how the corresponding populations differ from each other (Vandenberg & Lance 2000). This study consists of two groups of survey respondents: respondents from the IT cluster and respondents from outside the IT cluster. Hence, samples were divided into two groups based on organisation location.

SEM provides a framework to evaluate the differences between different populations. To assess the similarities and differences between the groups, the difference of the chi-square values and degrees of freedom of the baseline, the measurement weight and the measurement intercept models were considered (Hair et al. 2010).

Table 7.6: Chi-square Difference Test at Model Level

Model	X^2	df	X^2/df	X^2 diff.	df diff.	p-value
Baseline	2997.624	1435	2.089	-	-	0.000
Measurement weights	3075.260	1466	2.098	707.636	31	0.000
Measurement intercepts	3180.366	1506	2.112	105.106	40	0.000

Table 7.6.1 Nested Model Comparisons

(Assuming Model Unconstrained is Correct)

Model	DF	CMIN	P	NFI Delta-1	IFI Delta-2	RFI rho-1	TLI rho2
Measurement weights	31	77.636	.000	.006	.006	.001	.001
Measurement intercepts	71	182.742	.000	.013	.015	.003	.003

Table 7.6.2 Nested Model Comparisons

(Assuming Model Measurement Weights is Correct)

Model	DF	CMIN	P	NFI Delta-1	IFI Delta-2	RFI rho-1	TLI rho2
Measurement intercepts	40	105.106	.000	.008	.009	.002	.002

Tables 7.6, 7.6.1 and 7.6.2 provide results of the chi-square difference test. The chi-square difference for measurement weights versus measurement intercepts is statistically significant at the 0.000 level, which suggest that the two groups of IT organisations within and outside the cluster are different.

Table 7.7: Path Estimates and Significance Levels of IT Organisations by Group

Regression path	Organisations within the IT cluster		Organisations outside the IT cluster	
	Estimate	p-value	Estimate	p-value
Degree of openness → Innovation practices	0.63	***	0.73	***
Stakeholder engagement (Direct) → Innovation practices	-0.21	0.016	0.11	0.381
Stakeholder engagement (Indirect) → Innovation practices	0.65	***	0.17	0.115
Degree of openness → Knowledge spill-overs	0.36	***	0.41	0.026
Stakeholder engagement (Direct) → Knowledge spill-overs	0.14	0.173	0.27	0.184
Stakeholder engagement (Indirect) → Knowledge spill-overs	0.02	0.790	0.05	0.810
Innovation practices → Inbound innovation	0.71	***	0.85	***
Knowledge spill-overs → Inbound innovation	0.34	0.001	0.22	0.117
Knowledge spill-overs → Outbound innovation	0.06	0.474	0.18	0.479
Inbound innovation → Absorptive capacity	0.91	***	0.98	***
Innovation practices → Outbound innovation	0.89	***	0.74	***
Inbound innovation→ Innovation performance	0.79	***	0.85	***
Outbound innovation → Innovation performance	0.14	0.302	0.08	0.619
Absorptive capacity → Innovation performance	0.60	0.015	0.78	0.084

****Significant at 0.001*

Table 7.7 provides path estimates and significance levels for IT organisations within and outside the IT cluster. The organisations outside the IT cluster achieved higher estimates for paths degree of openness—Innovation practices, degree of openness—knowledge spill-overs, innovation practices—inbound innovation, inbound innovation—absorptive capacity and inbound innovation—innovation performance. The p-values suggest that these paths are significant at 0.001. The next section presented results of Kruskal-Wallis tests to illustrate the differences between the two groups organisations within the IT cluster and outside the IT cluster.

7.5 Non-Parametric Test Results

Chapter 5 presented univariate normality tests to check whether a dataset is properly modelled by a normal distribution. As suggested by Hair et al. (2010), departures from normality are assessed using two measures: kurtosis and skewness. However, research suggests use of non-parametric tests such as the Mann-Whitney U-test and the Kruskal-Wallis test to check whether differences between the two groups are significant. These non-parametric tests treat the data as non-normal. The Mann-Whitney U-test compares medians of the two groups and is limited to nominal values with only two values. The Kruskal-Wallis test is an extension of the earlier U-test, commonly used to compare three or more samples and test variance across groups.

In this study, the nominal variable is the location of an organisation and the possible values are within the IT cluster and outside the IT cluster. The responses are presented in numerical format using a 5-point Likert scale. As cluster-based effects are believed to influence organisations' OI activities and innovation performance, the Kruskal-Wallis test was used to compare statistically significant differences between the two independent groups (Ercan, Yazici & Yang 2007): IT organisations within and outside the IT cluster.

Results indicate significant differences with regard to the degree of openness between organisations within and outside the IT cluster (see Table 7.8). There are six statistically significant differences between the two groups. The mean scores highlight that organisations outside the cluster are less open in relation to maintaining up-to-date knowledge, strategies to encourage partnerships, managing networks, number of partners in other industries and continuously searching for new partners. There are significant differences with regard to direct stakeholder engagement in OI activities between organisations within and outside the IT cluster. The direct stakeholders of IT organisations in the IT cluster participated more compared with the other group. Interestingly, results indicate no significant difference between the two groups in relation to indirect stakeholder engagement. Although the mean score difference between the groups is less than 0.27, organisations in the IT cluster scored higher for indirect stakeholder engagement.

Table 7.8: Kruskal-Wallis Test of Significance Results for Degree of Openness and Stakeholder Engagement (Direct & Indirect) Constructs

Construct		Items	Within cluster (N = 245)	Outside cluster (N = 101)	Kruskal-Wallis Test	
			Mean score	Mean score	Chi-square	Asymp Sig.(2-tailed)
Degree of openness		DOP1 - Our organisation maintains up-to-date knowledge about processes, products and services.	4.39	3.84	24.405	0.000
		DOP2 - Our organisation's strategy focussed on open innovation, which encourages partnerships with other organisations.	3.81	3.47	4.238	0.040
		DOP3 - Our organisation manages its networks with other organisations through regular communication.	4.17	3.49	20.703	0.000
		DOP4 - Our organisation has large number of partners in various industries.	4.19	3.48	26.732	0.000
		DOP5 - Our organisation has standard business processes to search and acquire external knowledge/technology.	4.01	3.56	10.692	0.001
		DOP6 - Our organisation continuously search for potential partners through trade shows and seminars.	4.11	3.61	10.768	0.001
How important are the following stakeholders in open innovation projects?	Direct STK	STK1 – Employees	4.24	3.88	6.644	0.010
		STK2 – Customers	4.59	3.98	22.761	0.000
		STK3 – Technology providers	4.33	3.88	10.665	0.000
		STK4 – Government	4.07	3.58	11.312	0.001
	Indirect STK	STK5 – Education institutions	3.78	3.52	1.311	0.252
		STK6 – Start-up companies	3.58	3.31	2.200	0.138
		STK7 – Competitors	3.76	3.57	2.106	0.147

*Statistically significant at P < 0.05

Table 7.9: Kruskal-Wallis Test of Significance Results for Innovation Practice and Knowledge Spill-over Constructs

Construct	Items	Within cluster (N = 245)	Outside cluster (N = 101)	Kruskal-Wallis Test	
		Mean score	Mean score	Chi-square	Asymp. Sig.(2-tailed)
Innovation practices	OIP1 - Our organisation encourages employees to acquire potentially beneficial technologies/knowhow from external sources.	3.89	3.56	4.519	0.034
	OIP2 - Our organisation informs us about the significance of open innovation to organisation's survival.	3.92	3.45	12.305	0.000
	OIP3 - Our organisation rewards us for bringing in external technologies and knowledge to improve our products and services.	3.90	3.52	6.653	0.010
	OIP4 - Our organisation seeks feedback on proposed new products and services from employees not directly involved in R&D activities.	3.96	3.47	13.781	0.000
	OIP5 - Our organisation is supported by its partners in collaborative R&D projects.	3.70	3.42	3.540	0.060
	OIP6 - Our organisation facilitates access to external knowledge/technology to help develop new business opportunities to us.	3.85	3.64	1.641	0.200
Knowledge spill-overs	KSP1 - Our organisation considers external knowledge/technology to contribute to research and development of new products and services.	4.12	3.56	18.154	0.000
	KSP2 - Our organisation considers joint ventures/partnerships to create new knowledge/technology.	4.11	3.49	24.748	0.000
	KSP4 - Our organisation involves customers in the development of new products and services.	4.20	3.68	18.814	0.000
	KSP5 - Our products and services are developed or redesigned based on customer feedback and their needs.	4.34	3.64	27.583	0.000

*Statistically significant at $P < 0.05$

Results presented in Table 7.9 reveal four significant differences between the two groups. Organisations within the IT cluster scored high for innovation practices relating to informing their employees about the significance of OI, encouraging employees to acquire knowledge from external sources, seeking feedback on proposed new products and services from employees not directly involved in R&D and rewarding employees bringing in external knowledge. The differences between the two groups in relation to support from partners and facilitating access to external knowledge were found to be insignificant. The results highlight four statistically significant differences between the two groups organisations within the IT cluster and outside the IT cluster in relation to knowledge spill-overs. Overall, organisations within the IT cluster achieved higher mean scores for innovation practices and knowledge spill-overs.

Table 7.10: Kruskal-Wallis Test of Significance Results for Inbound and Outbound Innovation Constructs

Construct	Items	Within cluster (N = 245)	Outside cluster (N = 101)	Kruskal-Wallis Test	
		Mean score	Mean score	Chi-square	Asymp. Sig.(2-tailed)
Inbound innovation	INB1 - Our organisation is willing to buy other organisations IP rights such as trademarks and patents to support/improve internal business processes.	3.62	3.29	6.982	0.008
	INB2 - Our organisation buys IP rights from others to develop new products and services.	3.67	3.37	5.194	0.023
	INB3 - Our organisation upgrades existing technology to stay ahead of competitors.	4.16	3.75	7.324	0.007
Outbound innovation	OUB1 - Our organisation shares its knowledge with other organisations to create new knowledge/technology.	3.73	3.44	4.965	0.026
	OUB2 - Our organisation provides open access to other organisations to use our internal knowledge with little or no cost.	3.40	2.99	8.394	0.004
	OUB3 - Our organisation sells or licences its IP rights and patents, etc. to other organisations.	3.19	2.86	4.351	0.037
	OUB5 - Our organisation shares its knowledge with competitors to absorb resulting knowledge/technology.	3.46	3.20	4.142	0.042
	OUB6 - Our organisation prepares to sell IP rights such as trademarks and patents for profit.	3.31	3.14	1.508	0.219

*Statistically significant at P < 0.05

Results indicate significant differences with regard to inbound innovation activities between organisations within and outside the IT cluster (see Table 7.10). There are three statistically significant differences between the two groups. Organisations outside the cluster are less involved in relation to willingness, purchasing intellectual property rights and upgrading existing technology to stay ahead of competitors.

There are four significant differences in relation to outbound innovation activities. Organisations within the IT cluster scored high for sharing knowledge with others, providing open access, sharing knowledge with competitors and sale of intellectual property rights.

Results highlight differences in AC and innovation performance (see Table 7.11). The results indicate that organisations within the IT cluster have higher absorptive capacity and higher performances for process innovation, product innovation, service innovation and improving the number of IP rights. Organisations outside the IT cluster are comparatively behind in all aspects of innovation.

Table 7.11: Kruskal-Wallis Test of Significance Results for Absorptive Capacity and Innovation Performance Constructs

Construct	Items	Organisations within cluster (N = 245)	Outside cluster (N = 101)	Kruskal-Wallis Test	
		Mean score	Mean score	Chi-square	Asymp. Sig.(2-tailed)
Absorptive capacity	ABS1 - Our organisation has the capability to utilise new knowledge to organisation's benefit.	4.26	3.73	15.178	0.000
	ABS2 - Our organisation has the capability to develop new products and services by using external knowledge.	4.10	3.63	12.133	0.000
	ABS3 - Our organisation has the capability to develop alternative solutions by using external knowledge.	4.07	3.56	15.682	0.000
	ABS4 - Our organisation has the capability to integrate new knowledge with existing knowledge.	4.07	3.62	11.388	0.001
	ABS5 - Our organisation has the capability to redesign existing business processes through absorbing new knowledge.	4.05	3.66	7.986	0.005
Innovation perf. (last 3 years)	INNP1 – Process innovation	4.00	3.60	10.068	0.002
	INNP2 – Product innovation	3.97	3.54	10.426	0.001
	INNP3 – Service innovation	4.10	3.67	8.906	0.003
	INNP4 – Intellectual property rights	3.80	3.50	4.828	0.028

*Statistically significant at P < 0.05

7.6 Hypotheses Testing

The full research model and hypotheses are illustrated in Figure 7.14.

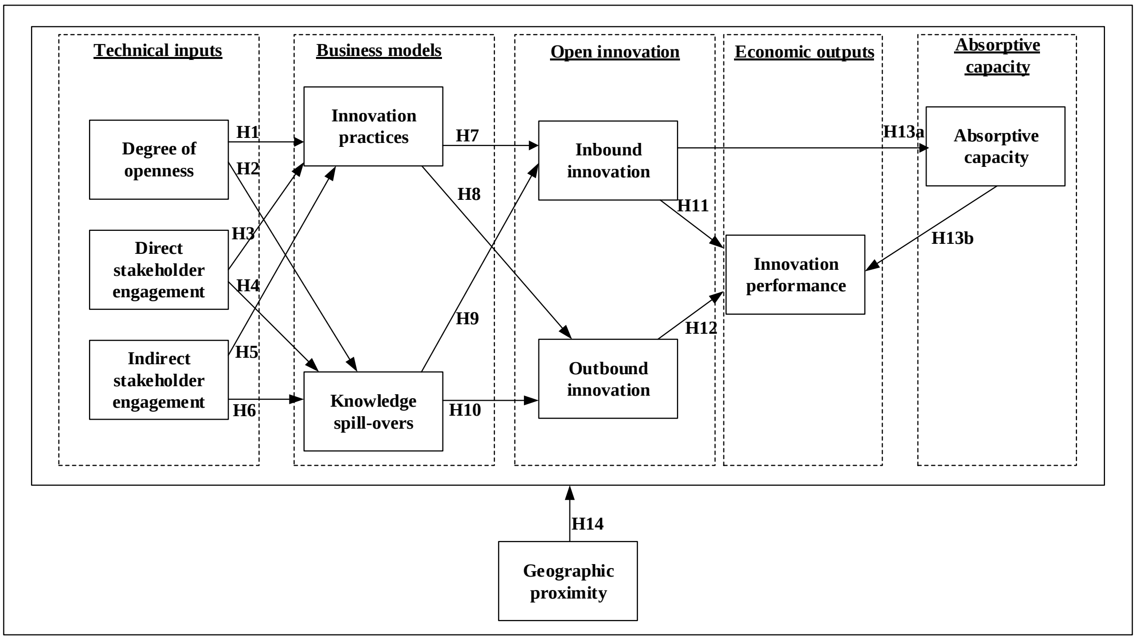

Figure 7.14: Full Research Model and Hypotheses

The research model consists of six theorised domains technical inputs (degree of openness, direct and indirect stakeholder engagement), business models (OI practices and knowledge spill-overs), OI (inbound innovation and outbound innovation), economic outputs (innovation performance), absorptive capacity and geographic proximity. Table 7.12 shows the structural paths of the structural model with estimates and significance intervals (see Table 7.5 for the structural paths and significance intervals for each hypothesis). Eleven hypotheses (excluding H14 – the effect of clustering) were found to be significant at a 95% confidence interval. A higher degree of inbound innovation and outbound innovation are positively related to innovation performance, as presented in the research model. The three hypotheses ‘H3: Direct Stakeholder engagement has a positive and significant relationship with innovation practices’, ‘H6: Indirect Stakeholder engagement has a positive and significant relationship with knowledge spill-overs’ and ‘H10: Knowledge spill-overs have a positive and significant relationship with outbound innovation’ were not supported.

Table 7.12: Hypothesis Testing

Hypothesis	Path Coefficient	P	Supported
H1: Degree of openness has a positive and significant relationship with innovation practices.	0.65	***	Yes
H2: Degree of openness has a positive and significant relationship with knowledge spill-overs.	0.40	0.012	Yes
H3: Direct stakeholder engagement has a positive and significant relationship with innovation practices.	-0.19	0.02	No
H4: Direct stakeholder engagement has a positive and significant relationship with knowledge spill-overs.	0.24	0.03	Yes
H5: Indirect Stakeholders engagement has a positive and significant relationship with innovation practices.	0.59	***	Yes
H6: Indirect Stakeholders engagement has a positive and significant relationship with knowledge spill-overs.	0.01	0.68	No
H7: Innovation practices have a positive and significant relationship with inbound innovation.	0.56	***	Yes
H8: Innovation practices have a positive and significant relationship with outbound innovation.	0.98	***	Yes
H9: Knowledge Spill-overs have a positive and significant relationship with inbound innovation.	0.54	***	Yes
H10: Knowledge spill-overs have a positive and significant relationship with outbound innovation.	-0.19	0.08	No
H11: Inbound innovation has a positive and significant relationship with innovation performance.	0.81	***	Yes
H12: Outbound innovation has a positive and significant relationship with innovation performance.	0.31	***	Yes
H13a: Inbound innovation has a positive and significant relationship with absorptive capacity.	0.95	***	Yes*
H13b: Absorptive capacity has a positive and significant relationship with innovation performance.	0.70	***	Yes
H14: Organisations within the IT cluster perform better in terms of open innovation and innovation performance compared with the organisations outside the IT cluster.	Yes		

****Significant at 0.001 *Results presented in table 7.16 for the mediation effect of absorptive capacity indicate that the Beta estimate for the relationship in between inbound innovation and innovation performance was not significant. A relevant description is presented in section 7.7.4.*

The constructs degree of openness, direct stakeholder engagement and indirect stakeholder engagement were theorised to promote innovation practices and knowledge spill-overs. However, the results show that the hypotheses H3 (on a positive relationship between direct stakeholder engagement and innovation practices) and H6 (on a positive relationship between indirect stakeholders and knowledge spill-overs) are not supported.

The constructs inbound innovation and outbound innovation were theorised to be directly influenced by innovation practices and knowledge spill-overs. The results indicate a positive relationship between innovation practices and inbound innovation (H7), and innovation practices and outbound innovation (H8). A positive relationship between knowledge spill-overs and inbound innovation is supported (H9). However, a positive relationship between knowledge spill-overs and outbound innovation (H10) is not supported. Hence, there is no significant direct relationship between the constructs knowledge spill-overs and outbound innovation. The significance was based on the p-value for the path "knowledge spill-overs—outbound innovation". In this case the p-value was found to be above 0.05. Hence, the negative relationship between knowledge spill-overs—outbound innovation was found to be insignificant.

The construct innovation performance was theorised to be influenced by the inbound and outbound innovation constructs. The results supported hypotheses H11 and H12, suggesting a direct significant relationship between OI (inbound and outbound) and innovation performance. Finally, the hypotheses 'H13a: Inbound innovation has a positive and significant relationship with absorptive capacity' and 'H13b: Absorptive capacity has a positive and significant relationship with innovation performance' are partially supported. The results indicate that an organisation's AC positively influences innovation performance. However, the results presented in table 7.16 for the mediation effect of absorptive capacity indicate that the Beta estimate for the relationship in between inbound innovation and innovation performance was not significant.

Finally, the multi-group analysis and Kruskal-Wallis tests found significant differences between organisations within and outside the IT cluster. Comparison of mean scores suggest that organisations within the IT cluster scored higher for all constructs. The results highlight the benefits of clustering and support hypothesis 'H14: Organisations within the IT cluster perform better in terms of open innovation and innovation performance compared with the organisations outside the IT cluster'.

7.7 Discussion

This section details the findings with regard to (1) the antecedent OI-related factors that influence IT organisations' innovation performance, (2) the effect of OI on innovation performance, (3) the mediating role of AC between OI and innovation performance (4) the impact of clustering on OI and innovation performance. The findings are presented based on the six domains of the literature presented in Chapters 2, 3 and 4.

7.7.1 Open Innovation and Innovation Performance

The literature points to the need for innovation and its role in supporting organisations' growth and performance (Chesbrough & Crowther 2006; Huang & Rice 2013; Markman 2016; Romer 2006; West, Vanhaverbeke & Chesbrough 2006). This study presented a conceptual framework and argued that innovation performance is a result of the efficiency and effectiveness of the OI activities (inbound and outbound) of an organisation. There has been much emphasis on the importance of OI and its role in improving innovation performance. OI is the purposive knowledge flows (inbound and outbound) that support an organisation's innovation efforts (Chesbrough 2003; Gassmann & Enkel 2004; West & Gallagher 2006); innovation performance is the result of the efficiency and effectiveness of innovation activities (Hanifah et al. 2017; Neely, Gregory & Platts 1995; Zizlavsky 2016). Scholars have paid considerable attention to sources of innovation and their impact on innovation performance (Jensen et al. 2007). Following this, later studies (Ebersberger et al. 2012; Greco, Grimaldi & Cricelli 2013; Laursen & Salter 2004) concluded that there is a positive relationship between OI activities and innovation performance.

Both inbound innovation *(*H11: *Inbound innovation has a positive and significant relationship with innovation performance)* and outbound innovation *(*H12: *Outbound innovation has a positive and significant relationship with innovation performance)* were found to have a significant impact on innovation performance. Hence, H11 and H12 were accepted. Overall, the conceptual framework presented in this study explained 84% of the variance in innovation performance. Table 7.13 compares the results of this with those of previous studies on OI and its relevance to innovation performance. These resuls are consistent with the previous studies.

Table 7.13: Findings of Previous Studies

Author	Context	Theory	R^2	Findings
Inauen & Schenker-Wicki 2011	141 R&D managers of organisations in German speaking countries	The relationship between the inbound innovation and innovation performance	0.215	Openness towards external sources can result in a higher level of innovation performance
Ebersberger et al. 2012	Community Innovation Survey data for Austria, Belgium, Denmark and Norway	The relationship between open innovation and innovation performance	0.16	A positive relationship between open innovation activities and innovation performance
Uduma, Ibeh & Ogbuji 2013	Based on 72 SMEs in the manufacturing sector in the UK	The effect of outbound innovation on innovation performance	0.920	Outbound open innovation positively influenced product performance
Vergara & Otero 2015	A sample of 1404 Colombian agrifood industries	The effect of the open innovation strategy	0.202	The positive impact of the OI strategy on innovative performance
Greco, Grimaldi & Cricelli 2015	A review of articles in European countries from 2003 to 2013	Linkage between OI actions and innovation performance	N/A	A positive relationship between OI activities and innovation performance

Earlier studies on data collected from European countries considered process, product, service and intellectual property as indicators to measure innovation performance. Inauen and Schenker-Wicki (2011) argued that OI strategies that focus on outside-in (inbound innovation) knowledge capturing influences innovation performance. The findings revealed evidence on the relationship between the openness of the outside-in process in R&D management and companies' innovativeness and innovation performance. Uduma, Ibeh and Ogbuji (2013) studied the role of inside-out (outbound innovation) activities on innovation performance. Their analysis indicated that the adoption of an outbound dimension of OI will positively affect product performance. Other studies by Ebersberger et al. (2012) and Vergara and Otero (2015) to understand the impact of OI on innovation performance also revealed a positive relationship. Greco, Grimaldi and Cricelli (2015) conducted an extensive literature review to examine the breadth and depth of OI and revealed that innovation performance can be improved by cooperating with other organisations.

The results in Table 7.13 support the theoretical background presented in Chapters 2 and 3. The conceptual framework presented in Chapter 3 indicates the influence of OI on innovation performance associated with improvements in processes, products, services and intellectual property rights. The results from earlier studies are similar to the results of this study, in relation to positive impact of inbound innovation and outbound innovation on innovation performance. Overall, the research model explained 84% of the variance in innovation performance, which can be placed with the range of comparable studies. The results are in line with the earlier studies (Greco, Grimaldi & Cricelli 2015; Vergara & Otero 2015).

In summary, inbound innovation activities have a positive and significant relationship with innovation performance. The path estimates in this model were interpreted to test the hypotheses presented in Figure 7.14. The path coefficient (0.81) for inbound innovation to innovation performance suggests that the value is statistically significant at the 0.001 level. These results are consistent with earlier studies on the effect of inbound innovation activities on innovation performance (Sisodia, Johnson & Gregoire 2013; Wang, Chang & Shen 2015). The positive influence of outbound innovation activities and its significant relationship with innovation performance was established. The path coefficient (0.31) for outbound innovation to innovation performance suggests that the value is statistically significant at the 0.001 level. These results highlight the importance of commercialising internal innovation to support internal R&D activities. Earlier studies (Ji et al. 2016; Lichtenthaler 2009) on the positive influence of outbound innovation reported similar outcomes.

7.7.2 Support of Innovation Practices and Knowledge Spill-overs for Open Innovation

This study conceptualised the influence of innovation practices and knowledge spill-overs in two ways: (1) a direct influence on OI (inbound and outbound) and (2) an indirect influence on innovation performance.

To acknowledge the existing theory, direct relationships between innovation practices and inbound and outbound innovation were hypothesised (Enkel & Grassmann 2007; Lichtenthaler 2011).

Innovation practices were hypothesised to have a positive influence on inbound innovation (*H7: Innovation practices have a positive and significant relationship with inbound innovation*) and outbound innovation (*H8: Innovation practices have a positive and significant relationship with outbound innovation*). The results presented in Table

7.12 reveal the positive influence of innovation practices on both inbound and outbound innovation, consistent with the hypotheses presented in Chapter 3.

This study hypothesised that knowledge spill-overs positively influence both inbound (*H9: Knowledge spill-overs have a positive and significant relationship with inbound innovation)* and outbound (*H10: Knowledge spill-overs have a positive and significant relationship with outbound innovation*) innovation. The results presented in Table 7.12 highlight the significant positive relationship between knowledge spill-overs and inbound innovation. However, the results do not support a positive relationship between knowledge spill-overs and outbound innovation. In fact, knowledge spill-overs are proven to negatively influence outbound innovation activities. To investigate the relationships presented in the structural model and the influence of innovation practices and knowledge spill-overs on innovation performance, indirect and total effects were examined (see Table 7.14).

Table 7.14: Standardised Effect of Innovation Practices and Knowledge Spill-overs

	Inbound innovation			Outbound innovation			Innovation performance		
	DE	IE	TE	DE	IE	TE	DE	IE	TE
Innovation practices	0.72	0.00	0.72	0.97	0.00	0.97	0.00	0.71	0.71
Knowledge spill-overs	0.35	0.00	0.35	-0.14	0.00	-0.14	0.00	0.26	0.26

DE: Direct effect; IE: Indirect effect; TE: Total effect

Table 7.14 indicates an indirect effect of innovation practices and knowledge spill-overs on innovation performance. The standardised indirect effect of innovation practices on innovation performance is 0.7, while the standardised indirect effect of knowledge spill-overs on innovation performance is 0.26. Although the relationship between knowledge spill-overs and outbound innovation was found to be insignificant (see Table 7.12), knowledge spill-overs have a standardised total effect on innovation performance.

In summary, investigation into the effects of innovation practices and knowledge spill-overs reveals three insights. First, inbound innovation activities involve facilitating inward knowledge flows, which include exploration and exploitation of external knowledge (Chesbrough 2003; Greco, Grimaldi & Cricelli 2015; Laursen & Salter 2006; Morris, Kuratko & Covin 2008). The results are consistent with the literature presented in Chapter 3 that innovation practices aimed at informing employees about the importance of OI, allowing stakeholders into R&D activities and rewarding employees for their participation support inbound innovation. Second, outbound innovation refers to inside-out knowledge flows for promoting knowledge sharing with the intent to commercialise internal innovations (Busarovs 2013; Enkel, Gassmann & Chesbrough 2009). Scholars have argued that knowledge flows support technology transfer and improve innovation performance (Dechezleprte et al. 2011; Glass & Saggi 2002). This study hypothesised a positive relationship between knowledge spill-overs and outbound innovation, but the results do not support this; in fact, knowledge spill-overs negatively influence outbound innovation. Third, consistent with previous studies (Von Hippel 1998; Boschma 2005a), this study identified an indirect effect of knowledge spill-overs on innovation performance. A recent study by Triguero and Fernandez (2018) on measuring the share of R&D investments by sector in different regions presented the positive influence of geographic proximity on product innovation. However, this study revealed the indirect effect of knowledge spill-overs on product innovation, process innovation, IP rights and service innovation. The results presented in relation to the positive effect of knowledge spill-overs on inbound and outbound innovation are original and not reported elsewhere.

7.7.3 Degree of Openness, Direct Stakeholder Engagement and Indirect Stakeholder Engagement for Innovation Practices and Knowledge Spill-overs

Innovation practices were theorised to be directly positively influenced by the degree of openness (*H1: Degree of openness has a positive and significant relationship with innovation practices*) and direct (*H3: Direct stakeholder engagement has a positive and significant relationship with innovation practices*) and indirect stakeholder engagement (*H5: Indirect stakeholder engagement has a positive and significant relationship with innovation practices*). The structural model and hypothesis testing results presented in Tables 7.7 and 7.12 indicate that H1 and H5 are supported at a 95% confidence interval. However, H3 is not supported. The results are significant, however, innovation practices are negatively influenced by direct stakeholder engagement. Thus, this study states that both degree of openness and indirect stakeholder engagement have a significant positive effect on innovation practices, while direct stakeholder engagement was proven to have a negative effect on innovation practices.

Innovation mainly comes from stakeholder engagement in innovation activities because of their genuine interest in the organisation's processes, products and services (Li, Mitchell & Boyle 2016; Owen & Goldberg 2010; Von Schomberg 2013). Stakeholder engagement promotes collaboration and identification of unique solutions (Tidd & Bessant 2013). According to Freeman et al. (2010), both direct and indirect stakeholders play an important role in innovation as their participation allows communication and development of shared goals (Andriof & Waddock 2002). In this context, scholars (Gould 2012; Greenwood 2007; Maak 2007) argue for innovation practices to facilitate interactions among stakeholders.

Stanislawski and Lisowska (2015) explain that degree of openness is the propensity to cooperate with other organisations. Innovation practices influenced by openness in cooperation and knowledge sharing across organisational networks support innovation (Beraud, du Castel & Cormerais 2012). Leminen, Turunen and Westerlund (2015) argue that 'Innovation practices in networks address foundational aspects, such as the transparency of innovation development and accessibility to innovation processes'.

Earlier studies assessed the benefits of innovation practices for OI at the individual firm level (Chesbrough 2006; Laursen & Salter 2006; Lichtenthaler & Lichtenthaler 2009) and called for studies into the benefits of OI practices in different operating contexts (Chesbrough 2006; Roper, Vahter & Love 2013). The motivation for the adoption of innovation practices is market related and the barriers for innovation practices are cultural diversity and organisational issues (Van der Vrande et al. 2009; Venturini, Verbano & Bron 2013). This study identified innovation practices as a consequence of degree of openness in innovation and provided preliminary evidence of its empirical significance in Chapter 3. The results in Tables 7.7 and 7.12 support previous arguments that stakeholder engagement (direct and indirect) and openness in innovation provides a rationale for innovation practices among organisations (Roper, Vahter & Love 2013). This study further extends the works of Parveen, Senin and Umar (2015), Rangus and Drnovsek (2013), Hung and Chiang (2010) and Lazzarotti, Manzini and Pallegrini (2011), who argued that openness is an important source of innovation practices aimed at OI. This study investigated the positive role of innovation practices on inbound and outbound innovation separately. In addition, the indirect effect of innovation practices on innovation performance has been investigated. The results indicate the indirect effect.

Knowledge spill-overs were theorised to be directly positively influenced by degree of openness (*H2: Degree of openness has a positive and significant relationship with knowledge spill-overs*), direct (*H4: Direct stakeholder engagement has a positive and significant relationship with knowledge spill-overs*) and indirect (*H6: Indirect stakeholder engagement has a positive and significant relationship with knowledge spill-overs*) stakeholder engagement. The hypotheses testing presented in Table 7.12 indicates that H2 and H4 are supported and significant at a 95% confidence interval. H6 was not supported as the p-value is not significant at the 95% confidence interval.

Degree of openness can range from closed to multiple levels of openness (both inward and outward orientation) involving all transactions relating to knowledge sharing in the innovation area (Drechsler & Natter 2012; Michelino et al. 2014). Openness may vary with the level of control participants have over access to technologies and exploitation of the knowledge (Boudreau 2008; Petrusson, Rosen & Thornblad 2010). While openness focusses on the level of participation in knowledge-sharing activities, it is stakeholder engagement that stimulates knowledge transfer (Gould 2012). Chesbrough's (2003) OI model reiterates the need to harness external knowledge through stakeholder engagement. This study confirms the positive role of openness and direct stakeholder engagement in knowledge spill-overs. These results are in line with the arguments presented in Chapter 3; however, the importance of indirect stakeholder engagement is not supported.

7.7.4 The Mediating Effect of Absorptive Capacity Between Inbound Innovation and Innovation Performance

The mediating effect is interference of a third variable between other related constructs (Hair et al. 2010). In this study, it is hypothesised that AC mediates the relationship between inbound innovation and innovation performance (H13a and H13b). To understand the mediating effect of AC, this study tested the structural model with AC by drawing paths as shown in Figure 3.1 (see Chapter 3).

As a starting point, the direct path between inbound innovation and innovation performance was tested. The results presented in Table 7.15 indicate that the p-value is significant and inbound innovation has a direct effect on innovation performance. Based on these findings, the structural model was revised by creating additional paths between inbound innovation and AC, and AC and innovation performance.

Table 7.15: Summary of Estimates without Absorptive Capacity

Relationship	Beta Estimate	SE	CR	P-value	Result
Inbound innovation → Innovation performance	0.734	0.094	7.827	0.000	Significant

Table 7.16: The Summary of Estimates with Absorptive Capacity

Relationship	Beta Estimate	SE	CR	P-value	Result
Inbound innovation → Innovation performance	0.048	0.185	0.261	0.794	Insignificant
Inbound innovation → Absorptive capacity	0.880	0.064	13.790	0.000	Significant
Absorptive capacity → Innovation performance	0.655	0.172	3.808	0.000	Significant

The results of the revised model suggest that the p-value for the path, inbound innovation to innovation performance is insignificant (see Table 7.16). However, the p-values for the paths (1) inbound innovation to AC and (2) AC to innovation performance indicate these paths are significant and confirm the partial mediating role of AC.

Scholars (Iyengar, Sweeney & Montealegre 2015; Junni & Sarala 2013; Tzokas et al. 2015) have explored and widely tested the concept of AC in the context of innovation performance. Lane, Koka and Pathak (2006) viewed AC as an important element in achieving innovation performance. The literature also points to the relationship between an organisation's AC and innovation performance (Cohen & Levinthal 1990; Kostopoulos et al. 2011). The results in Tables 7.15 and 7.16 confirm the partial mediating role of AC. These results are consistent with arguments that AC plays a mediating role between OI and innovation performance by integrating external knowledge into its innovation processes (Arbussa & Coenders 2007).

7.7.5 The Effect of Clustering on Open Innovation and Innovation Performance

This study investigated whether organisation location has any influence on their efforts to explore and exploit external knowledge from other organisations. The literature reveals the role of clustering in facilitating interactions among organisations, which are critical for purposive knowledge flows, both inward and outward (Chesbrough 2006). These interactions are considered crucial, as organisational competence in searching for and sourcing external knowledge influences innovation performance (Van de Vrande et al. 2009).

Section 7.4 presented a multi-group analysis to test differences between the two groups of survey respondents: those within and those outside the IT cluster. The samples were divided into two groups based on organisation location and a multi-group analysis was conducted as suggested by Hair et al. (2010). This study hypothesised that organisations within the IT cluster perform better in terms of OI and innovation performance than those outside the IT cluster (H14).

Tables 7.6, 7.6.1 and 7.6.2 (Section 7.4) provide the results of the chi-square difference test for the measurement weights versus measurement intercepts models. The chi-square difference for measurement weights versus measurement intercepts is statistically significant at the 0.000 level, which suggest that the two groups (within and outside the cluster) are indeed different. As cluster-based effects are believed to influence organisational OI activities and innovation performance, the Kruskal-Wallis test was used to compare statistically significant differences between the two independent groups (Ercan, Yazici & Yang 2007).

The Kruskal-Wallis test can detect minute differences between groups. It is particularly useful when data sets are of different sizes (Hart 2001). As the two groups consist of different sample sizes, a Kruskal-Wallis test was used to check whether the differences between the two groups are significant. Results indicate significant differences between the two groups (see Tables 7.8, 7.9, 7.10 and 7.11). To expedite further, the mean scores of the two groups for inbound innovation, outbound innovation and innovation performance are compared (see Tables 7.10 and 7.11). The analysis indicates that organisations outside the cluster are less involved in relation to inbound innovation, outbound innovation and innovation performance. These results highlight the important role of clustering in facilitating interactions among organisations within a close proximity (Nie & Sun 2014; Porter 2000) that promote purposive inward knowledge flows. According to Chesbrough (2006), organisations within a geographical proximity will have high interaction opportunities (Laursen & Salter 2006). The Mann-Whitney U-test results suggest differences between the two groups and the comparison of mean scores support H14.

In summary, this study tested the full research model presented in Figure 7.14 and presented results and findings. Overall, the results are similar to the previous research on OI and innovation performance except for H3 (Direct stakeholder engagement has a positive and significant relationship with innovation practices), H6 (Indirect stakeholder engagement has a positive and significant relationship with knowledge spill-overs) and H10 (Knowledge spill-overs have a positive and significant relationship with outbound innovation). The results relating to H3 and H10 are significant but negative, as opposed to the literature presented in Chapters 3 and 4. Although there is a positive relationship between indirect stakeholder engagement and knowledge spill-overs, the results were found to be insignificant. This study extended the previous research by examining the antecedent OI-related factors that influence IT organisations' innovation performance, the effect of OI on innovation performance, the mediating role of AC between OI and innovation performance and the impact of clustering on OI and innovation performance.

7.8 Summary

The goal of this chapter was to analyse and discuss the results presented in Chapter 6. Based on the earlier results, a structural model was designed to test the hypotheses presented in Chapter 3. The results of the structural model revealed positive relationships among the constructs except for indirect stakeholders and knowledge spill-overs. The mediating role of AC between inbound innovation and innovation performance was established. A multi-group analysis revealed a significant difference between the two groups: organisations within the IT cluster and organisations outside the IT cluster. Non-parametric tests also confirmed significant differences. The comparison of mean scores highlighted the role of clustering on OI (inbound and outbound) and innovation performance. The next chapter summarises the key findings of this PhD study and presents limitations, implications and future research opportunities.

Chapter 8: Summary and Conclusion

8.1 Introduction

The aim of this chapter is to highlight the key findings of the study. It describes how this PhD study attempted to address the research questions presented in Chapter 1. It also presents contributions, limitations and future research opportunities.

To address the research questions presented in Chapter 1, this study elaborated the importance of purposive knowledge flows (OI) and their role in innovation performance. Based on previous studies, a research model was developed to assess the role of OI and clustering and the mediating effect of AC on innovation performance. The developed model was empirically tested. The results indicate that the construct in the model explained 84% of the variance in innovation performance. This chapter is organised into five sections. Section 8.2 revisits the research questions and details how these were addressed in this study. Section 8.3 elaborates both theoretical and practical contributions. Section 8.4 outlines limitations of this study and future research opportunities. Section 8.5 presents concluding remarks.

8.2 Research Questions Revisited

Based on an extensive literature review, the research problems, gaps and rationale presented in Chapter 1, five research questions were framed: What is open innovation and how do we measure it? Do the degree of openness, stakeholder engagement, innovation practices and knowledge spill-overs affect open innovation? Do inbound and outbound innovation activities drive innovation performance in IT organisations? Does the absorptive capacity of IT organisations influence innovation performance? Does clustering of IT organisations affect innovation performance?

Founded on Chesbrough's (2006) OI model, to investigate and address the five research questions, a research model was developed (see Chapter 3), which considers an internal technology base and an external technology base as technical inputs leading to OI and innovation performance as economic outputs. In view of earlier studies, this study presented research hypotheses to test the direct positive effects of the degree of openness and stakeholder engagement on innovation practices and knowledge spill-overs. Then, a positive relationship between OI constructs (inbound and outbound) and innovation performance was hypothesised. As AC was proven to be critical for utilising externally sourced knowledge for innovation performance (Cohen & Levinthal 1990; Laursen & Salter 2006), the mediating effect of AC was hypothesised. Various cluster theories emphasise the interaction and collaboration opportunities clusters offer. Considering the role it plays in diffusion of knowledge, relevant hypotheses were presented to test the impact of geographic proximity on OI and innovation performance. The full research model and relevant hypotheses are presented in Figure 8.1.

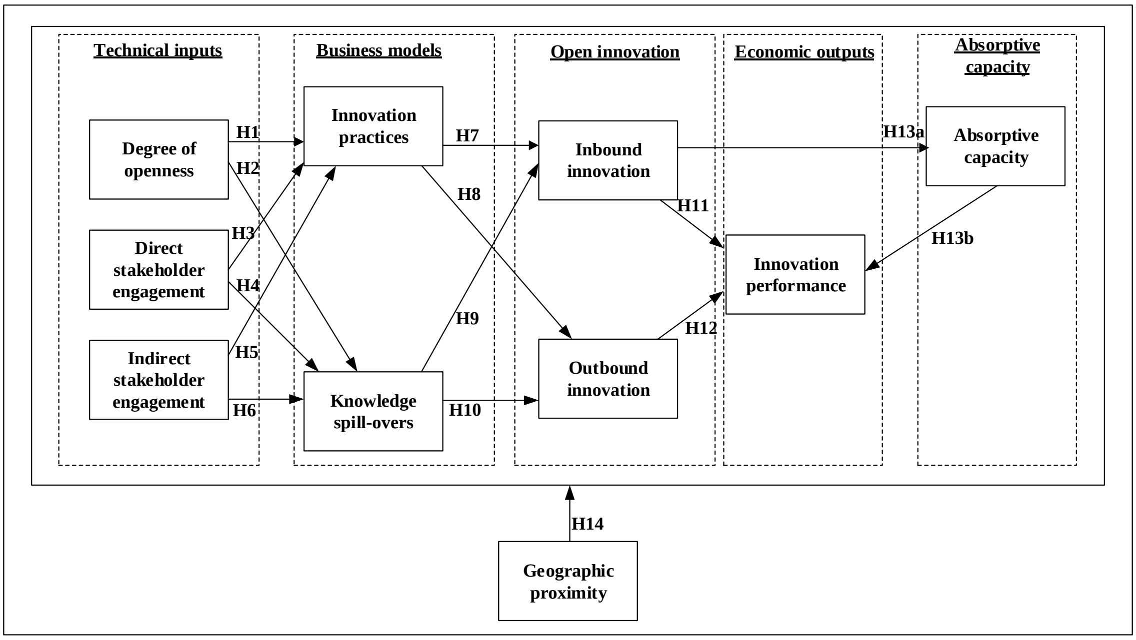

Figure 8.1: Research Model Revisited

A total of 15 hypotheses including H13a and H13b were presented in Chapter 3. Of these, 11 were supported by a 95% confidence interval excluding H14 on geographic proximity (see Table 7.12). The role of geographic proximity was tested using multi-group analysis and Kruskal-Wallis non parametric tests. The results support Hypotheis 14. These results offer an opportunity for a meaningful discussion to address the research questions.

8.2.1 What Is Open Innovation and How Do We Measure it?

Chesbrough (2006, 2003) explained that open innovation is about facilitating inward and outward knowledge flows to promote collaborative innovation. However, Van de

Vrande et al. (2009) later classified open innovation into inbound innovation and outbound innovation. Inbound innovation involves with promoting inward knowledge flows and benefiting from it. Whereas, outbound innovation activities are associated with sharing internal knowledge with other firms and commercialising internal innovations to generate profits that can be diverted for internal research and development efforts. Based on chesbrough's OI model and an extensive literature review, this study operationalised various constructs degree of openness, direct stakeholder engagement, indirect stakeholder engagement, innovation practices and knowledge spill-overs to measure inbound and outbound innovation. The research model presented in figure 8.1 shows the constructs and their positive influence on inbound and outbound innovation. The results indicate that both inbound and out innovation can be measured with the proposed research model. The positive influence of various constructs on inbound and outbound innovation are detailed in the following sections.

8.2.2 Do the Degree of Openness, Stakeholder Engagement, Innovation Practices and Knowledge Spill-overs Affect Open Innovation?

Ever since Chesbrough introduced the OI concept, studies have argued for the role it plays in improving innovation performance; however, the majority are conceptual in relation to the antecedents. Consistent with Chesbrough's views, this study examined the positive relationship between technical inputs (degree of openness and stakeholder engagement) and innovation practices and knowledge spill-overs. Hence, the second research question of this study was formulated as '*Do the degree of openness, stakeholder engagement, innovation practices and knowledge spill-overs affect open innovation?'*

To address this research question, three technical inputs (degree of openness, direct stakeholder engagement and indirect stakeholder engagement) were theorised and hypothesised to positively influence innovation practices and knowledge spill-overs. The degree of openness was initially operationalised to consist of seven variables: access to new knowledge and technologies, innovation strategies, openness and flexibility, network building, partner variety and cooperation. However, during the instrument validation process, it was found that DOP7 did not fit into the openness construct. The other constructs in the technical inputs domain—direct stakeholder engagement and indirect stakeholder engagement—were validated and used in the structural model.

The results of the structural model revealed several positive and negative effects on innovation practices and knowledge spill-overs (see Table 7.12). The degree of openness and indirect stakeholder engagement have a positive and significant relationship with innovation practices, while direct stakeholder engagement has a negative and significant relationship with innovation practices. Both the degree of openness and the direct stakeholder engagement constructs have shown positive relationships with knowledge spill-overs. Interestingly, indirect stakeholder engagement has shown a positive link with knowledge spill-overs, but the results were insignificant.

The construct innovation practices was operationalised with six variables and the knowledge spill-overs construct was operationalised with five variables initially. During the validation process (EFA), one of the variables (KSP3) from knowledge spill-overs was found to be associated with the innovation practices construct. Hence, this item was excluded from further analysis.

The results of the structural model indicate a positive link between innovation practices and OI constructs (inbound and outbound). Knowledge spill-overs positively influenced inbound innovation, but showed a negative relationship with outbound innovation. However, both have an indirect effect on OI.

Earlier studies highlighted the role of OI in innovation performance, but offered limited evidence in relation to the factors that positively influence OI; hence, the question '*Do the degree of openness, stakeholder engagement, innovation practices and knowledge spill-overs affect open innovation?'* This study revealed positive relationships among the constructs and indirect effects of innovation practices on innovation performance. These results confirmed that degree of openness, stakeholder engagement, innovation practices and technological spill-overs affect OI constructs inbound and outbound innovation.

8.2.3 Do Inbound and Outbound Innovation Activities Drive Innovation Performance in IT Organisations?

Earlier studies argued for the role of OI in improving innovation performance. This study reviewed the OI to separate purposive knowledge flows into inbound innovation (outside-in flows) and outbound innovation (inside-out flows). Considering the relationship between various constructs presented in the previous section, this study tested the positive relationship between OI constructs and innovation performance.

The inbound innovation construct was operationalised with three variables and the outbound innovation construct was operationalised with seven variables. However, during the instrument validation process (EFA), two variables (OUB4 and OUB7) from the outbound innovation construct were found to have cross-loadings with inbound innovation. As a result, they were removed from further analysis.

The results of the structural model indicate a positive and significant relationship between both the OI constructs and innovation performance. Earlier studies presented empirical results to support their argument on the role of OI in innovation performance, but these studies were limited to operationalising inbound and outbound innovation and their relevance to innovation performance. This study operationalised the constructs presented in Figure 8.1 and tested their relevance to OI and innovation performance. The findings of this research strengthen the argument for OI as a source of innovation performance. The inbound innovation activities involving knowledge exploration and exploitation were proven to support internal innovation. Outbound innovation activities aimed at commercialising internal knowledge also supported internal research and development activities; hence, the research question, '*Do inbound and outbound innovation activities drive innovation performance in IT organisations?'* can be positively answered.

8.2.4 Does the Absorptive Capacity of IT Organisations Influence Innovation Performance?

The literature presented in Chapters 2 and 3 highlighted the importance of AC in absorbing and utilising knowledge in innovation processes. Previous studies have found the effect of AC on innovation performance (Iyengar, Sweeney & Montealegre 2015; Junni & Sarala 2013; Tzokas et al. 2015) in the context of closed innovation.

Considering the role of OI in improving innovation performance, this study argued that inbound innovation facilitates outside-in knowledge flows, but the organisation's capability to assimilate and transform external knowledge determines the level of innovation performance. Based on this argument, the mediating effect of AC in between inbound innovation and innovation performance was tested.

AC was operationalised with five variables on capability to adapt external knowledge and fuse and develop new products and services. The paths inbound innovation to AC and AC to innovation performance were found to be positive and significant.

8.2.5 Does Clustering of IT Organisations affect Innovation Performance?

Scholars have pointed out that organisations in a cluster share common characteristics and viewed them as regional innovation systems because of the interaction opportunities they provide to enable relationships and joint ventures among participants (Brusco 1992; Enright 1996; Nie & Sun 2014; Sammarra & Biggiero 2001). Earlier studies examined the role of clustering on innovation performance from the closed innovation perspective. Not only have very few studies considered the OI perspective, these studies relied on secondary data or are limited to a specific context (Giusti, Alberti & Belfanti 2017; Huang & Rice 2013; Terstriep & Luthje 2009). This study presented an argument that interactions among organisations with similar business interests in a cluster promote OI and innovation performance; hence, the research question, *'Does clustering of IT organisations affect innovation performance?'*

To test the relevance of clustering on OI and innovation performance, a multi-group analysis was conducted using an SEM framework. This helped to assess the differences between the two groups of survey respondents (those from the IT cluster and those outside the IT cluster). The chi-square difference for measurement weights versus measurement intercepts was statistically significant at the 0.000 level, which suggests that the two groups are different.

To expedite further, a Kruskal-Wallis test was conducted for all the variables presented in the full measurement model. The results indicated that differences between the two groups are significant. A comparison of the mean scores of the two groups presented significant differences in relation to OI and innovation performance. The organisations within the IT cluster achieved higher mean scores than the other group in all aspects.

The positive impact of clustering on OI and innovation performance has been proven, and the research question can be answered in the positive: organisations within geographic proximity show higher innovation performance due to better interaction and collaboration opportunities.

8.3 Research Contributions

8.3.1 Theoretical Contributions

This study makes several contributions to the literature on OI, innovation performance, AC and IT clusters.

First, the research model attempted to show the relevance of various constructs to OI and innovation performance. The results of this study highlighted the positive impact of degree of openness and stakeholder engagement on innovation practices and knowledge spill-overs. The developed research model also revealed the positive links of OI constructs with innovation practices and knowledge spill-overs. This adds to the body of knowledge on the link between technical inputs and OI. The indirect effects on innovation performance established the significance of innovation practices and knowledge spill-overs.

Second, the positive influence of inbound innovation and outbound innovation (OI) on innovation performance was examined. The results support the positive impact of OI in improving processes, products, services and intellectual property rights. The model explains 84% of the variance in innovation performance of the sample firms.

Third, this PhD study developed a framework on the basis of earlier fragmented work on OI constructs and innovation performance from the strategic management theories: RBV, RV and AC. Hence, this study not only utilised earlier research but integrated AC into the research model.

Fourth, the OI concept is built on the core principles of interaction, interdependence and exchange of ideas and knowledge sharing. The findings of this research elaborated the role of cluster-based effects in enabling OI among organisations by location. This research provides supporting results in relation to the environment through which OI benefits can be improved. Results indicate that organisations in a cluster are more involved in OI activities. This suggests the supporting role clusters play in exploring and exploiting external knowledge, commercialising internal innovations and sharing knowledge with other organisations.

Finally, this study provides a validated framework to evaluate OI and the innovation performance of organisations. The tested scales can be used in future research to explore the roles of variables in a different environment.

8.3.2 Practical Contributions

From a practical point of view, this study provides valuable knowledge to managers and policy makers on adopting appropriate practices to enhance OI and innovation performance.

First, innovations are seen as critical for organisations' survival in a dynamic environment. However, organisations need to make significant investments in R&D activities, which may not always yield returns. In such a situation, managers are faced with a question: 'Are there ways to explore and exploit external knowledge?' This study presented an extensive literature review on OI constructs. In particular, inbound innovation activities involve exploration and exploitation of external knowledge. In-depth knowledge on inbound innovation helps managers to adopt appropriate steps to access external knowledge to fuel internal R&D and achieve cost savings on innovation-related investment.

Second, internal innovations and knowledge will have little significance for a period of time. Managers are faced with the questions 'Is it harmful to share our knowledge with others?' and 'Can we still benefit from the sale of some of our innovations?' This study argued that organisations should move away from the closed innovation model and presented arguments for commercialising intellectual property rights. The results supported the role of outbound innovation on innovation performance. Managers can utilise this knowledge to commercialise internal innovations and intellectual property rights. This additional revenue can be diverted to support internal R&D activities.

Third, the OI model illustrates the need for purposive knowledge flows. However, the organisation's capability to assimilate external knowledge into its innovation mechanisms enhances innovation performance. This study established the mediating effect of AC on innovation performance. Although, the mediating effect of AC was found to be partial, Managers can still benefit from this knowledge and develop appropriate practices to not only absorb but also effectively utilise external knowledge into their innovation processes.

Fourth, the IT industry in India makes a significant contribution to the national economy by providing employment and economic opportunities. The local government initiated an IT cluster and offered incentives to promote the establishment of IT organisations within a designated zone, including provision of the necessary infrastructure. However, the innovation-related benefits have not been explored in the local context. This study examined the role of clustering in improving innovation performance. The results can be used by local governments for developing policies to promote regional clusters.

Finally, IT organisations in India are mainly low-cost IT service providers for overseas organisations, established to benefit from government incentives. In recent years, they have been faced with significant competition from other countries. For their survival and future growth, they need to improve their innovation performance. This study investigated the open innovation mechanism and its influence on innovation performance. Moreover, the comparison of data between the two groups organisations within and outside the IT cluster reveal significant differences and the positive impact of geographic clustering. Managers can utilise the study results to improve cluster-based interactions for purposive knowledge flows.

8.4 Limitations and Future Research Opportunities

This study identified several limitations and future research opportunities.

First, this study examined the level of openness in relation to OI in IT organisations; it did not investigate various strategies and the relevance of these to OI and innovation performance. The literature points to the role of technologies in enabling openness (Nketia 2016; Whittington et al. 2011). Future research could reveal the role of technologies in enabling openness and the relevance of various strategies to OI and innovation performance.

Second, OI is comprised of two constructs: inbound and outbound innovation. The current study focusses on the mediating effect of AC for only inbound innovation. Outbound innovation activities involve voluntary disclosure of internal knowledge. The organisation's desorptive capacity positively influences innovation performance (Lewandowska 2015). However, outbound innovation processes in the context of desorptive capacity are little explored (Enkel, Gassmann & Chesbrough 2009). Future research could elaborate the mediating effect of desorptive capacity on innovation performance.

Third, the survey questionnaire consisted of 44 questions in addition to demographic variables. However, during the validation process, a total of four items from degree of openness, knowledge spill-overs and outbound innovation constructs were dropped. Future research consisting of these items would help reveal their relevance to innovation performance.

This study adopted survey questions from the previous studies which attempted to study the role of openness, stakeholder engagement, innovation practices and knowledge spill-overs in relation to developing new processes, products and services together. Earlier studies focused on understanding innovation related activities and their influence on overall innovation effectiveness in organisations. As a result these studies adopted questions to understand organisations' willingness to work and share its knowledge with other organisations to develop new processes, products and services. Future research into studying processes, products and services related innovations individually would help reveal important information on the innovation performance achieved through open innovation activities.

Fourth, this empirical study provided an overview of the variables under investigation. The results on OI, AC, innovation performance and the effect of clustering were based on the opinions of respondents in the current setting and did not permit investigation of the longitudinal effects. The higher-order resource of OI (inbound and outbound) builds on many other constructs, which could take time to develop. Items in relation to innovation performance are concerned with the non-economic performance of processes, products, services and intellectual property rights over the last three years. Although recent data provide valuable insights, a longitudinal study would reveal important patterns in the variables over time and an understanding of cause-and-effect relationships (Bryman & Bell 2011; Cresswell 2009; Masani 2001); in particular, the long-term effects of OI.

Fifth, a quantitative data collection approach was adopted in this study and a questionnaire distributed to organisations within and outside the IT cluster. While a quantitative data collection approach helps to synthesise hypotheses and causal relationships, it fails to offer insights into individual experiences (Bryman & Bell 2011; Myers 1997; O'Leary 2005). Adopting a mixed method approach in future research would allow a comprehensive evaluation of the problem and interpretation of the data (Creswell 2009).

Sixth, the main limitation with this research is that it utilises data collected from IT organisations within and outside the Hyderabad IT cluster. Future research into comparison of data collected from IT organisations in various IT clusters in India could provide an opportunity to elaborate the significance of clustering and its role in promoting purposive knowledge flows.

Finally, this research collected data from only one country. Edwards, Delbridge and Munday (2005) suggest that socio-cultural background has an impact on innovation. Future research into comparison of data collected from the organisations of IT clusters of two or more countries would allow a higher level of understanding on the impact of clustering on OI and innovation performance in different contexts.

8.5 Concluding Remarks

This PhD study bridged a research gap by developing a theoretical framework to investigate the role of OI on innovation performance.

The results of this study detailed the importance of OI and its support to innovation performance. This study contributes to both theory and practice on OI, innovation performance, AC and IT clusters. This study developed and validated an instrument to evaluate the indicators of technical inputs-related constructs (degree of openness and stakeholder engagement) that positively affect innovation practices and knowledge spill-overs to enable OI and improve innovation performance.

Both outside-in (inbound) and inside-out (outbound) knowledge flows were proven to improve innovation performance. The empirical results provided evidence of the mediating effect of AC on innovation performance and the relevance of clustering on both OI and innovation performance. Hence, the potential contribution of OI, AC and clusters to innovation performance may increase in future, presenting grounds for future research on OI and innovation performance.

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Appendices

Appendix A: Invitation to Participate in a Research Project

RMIT UNIVERSITY

INVITATION TO PARTICIPATE IN A RESEARCH PROJECT

PARTICIPANT INFORMATION

Project Title: *"The* Competitive Advantage of IT Clusters: Assessing technological spill-overs and open innovation"

Investigators:

(1) Prof. Prem Chhettri

(2) Prof. Alemayehu Molla

(3) Srimannarayana Grandhi

Dear Participant,

You are invited to participate in a research project being conducted by RMIT University. Please read this sheet carefully and be confident that you understand its contents before deciding whether to participate. If you have any questions about the project, please ask one of the investigators.

Who is involved in this research project? Why is it being conducted?

My name is Srimannarayana Grandhi and I am doing a PhD research in the School of Business IT & Logistics, RMIT University, Melbourne. My supervisors are Prof. Chhettri and Assoc. Prof. Molla. This project has been approved by the RMIT Human Research Ethics Committee. The primary goal of this research is to investigate the role of clusters in facilitating technological spill-overs and open innovation and understand ways to foster open innovation.

Why have you been approached?

This survey is to be completed by the employees working in IT organisations. If you are over 18 years of age and an IT employee working in leadership, sales, technology, consulting, corporate function, business process, research and development, education and training, you are invited to participate in this PhD research project being conducted through RMIT University.

What is the project about? What are the questions being addressed?

About 500 IT employees from the Hyderabad IT cluster and outside the cluster will be recruited for this study. The purpose of the research is to investigate the relevance of co-location of IT firms to technological spill-overs and open innovation. The participants will be asked to share their knowledge about their organisation's ability to access new knowledge, whether the knowledge is sourced internally or externally for their research and their organisation's current practices relating to open innovation.

If I agree to participate, what will I be required to do?

If you decide to participate, you will be asked to complete a questionnaire which will take approximately 20 minutes to complete. You will be provided with a web link to access your questionnaire online (e.g., via PC or tablet using a secure online server). This questionnaire includes questions about your organisation’s willingness to cooperate with other organisations, innovation mechanisms and practices in your organisation. Examples of questions include, "Our organisation maintains up-to-date knowledge” and "our organisation has large number of partners in different sectors". Prior to completing the questionnaire, you will also be asked for some demographic details. We will not collect any identifiable information.

What are the benefits associated with participation?

Studying the Hyderabad IT cluster can reveal important information, which can be used by the other governments to understand their role in the creation of new IT clusters and help them to improve innovation performance of organisations in a cluster to achieve economic growth.

What will happen to the information I provide?

The responses you provide to the survey will be stored on the RMIT University server. Once we have completed our data collection and analysis, we will import the data we collect to the RMIT server where it will be stored securely for a period of five (5) years. Data will be reported as an aggregate data. Therefore, individuals will not be identified. Your privacy and confidentiality will be strictly maintained in such a manner that you will not be identified in the thesis report or publication. As participants' details are not recorded, any information that you provide can be disclosed as aggregate data only if (1) it is to protect you or others from harm, (2) if specifically required or allowed by law, or (3) you provide the researchers with written permission. Data will be only seen by the researcher and supervisors who will also protect you from any risks.

At the conclusion of the project, a summary of the results and associated reports will be made available should you request for it. If you wish to receive the results of this study, then please email your contact details to one of the investigators. The contact details will be used strictly for dissemination of results and will not be passed to third party and will be purged once the objective is met. The final results will also be reported in a thesis to be submitted for Mr. Srimannarayana's PhD degree, and as appropriate, in papers for presentation at conferences or for publication in scientific journals. Because of the nature of data collection, we are not obtaining written informed consent from you. Instead, we assume that you have given consent by your completion and return of the questionnaire.

What are my rights as a participant?

As a participant, you have the right to withdraw at any time and to have any questions answered at any time. Your participation in this research will help identify the role of clusters in technological spill-overs and open innovation, which can be used by the IT organisations to foster innovation and to enhance overall performance.

What are the possible risks or disadvantages? Whom should I contact if I have any questions?

There are no anticipated risks associated with participation. However, if you are unduly concerned about your responses to any of the questionnaire items or if you find participation in the project distressing, you should contact *the Ethics Officer, Research Integrity, Governance and Systems, RMIT University, GPO Box 2476 VIC 3001. Tel: (03) 9925 2251 or email* human.ethics@rmit.edu.au as soon as convenient. The Ethics Officer will discuss your concerns with you confidentially and suggest appropriate follow-up, if necessary.

Security of the website

Users should be aware that the World Wide Web is an insecure public network that gives rise to the potential risk that a user's transactions are being viewed, intercepted or modified by third parties or that data which the user downloads may contain computer viruses or other defects.

Security of the data

This project will use an external site to create, collect and analyse data collected in a survey format. The site we are using is https://www.qualtrics.com. If you agree to participate in this survey, the responses you provide to the survey will be stored on a host server that is used by Qualtrics. No personal information will be collected in the survey so none will be stored as data. Once we have completed our data collection and analysis, we will import the data we collect to the RMIT server where it will be stored securely for five (5) years. The data on the Qualtrics host server will then be deleted and expunged.

Thank you for your assistance and for giving us your time to participate. We value your contribution to this research.

Yours sincerely

Srimannarayana Grandhi, Prof. Prem Chhettri & Prof. Alemayehu Molla.

If you have any concerns about your participation in this project, which you do not wish to discuss with the researchers, then you can contact the Ethics Officer, Research Integrity, Governance and Systems, RMIT University, GPO Box 2476V VIC 3001. Tel: (03) 9925 2251 or email human.ethics@rmit.edu.au

Appendix B: Ethics Approval

RMIT UNIVERSITY

Deputy Pro Vice-Chancellor
(Research & Innovation)
College of Business

GPO Box 2476
Melbourne VIC 3001
Australia

Tel: +61 3 9925 5432
Fax: +61 3 9925 5624

Notice of Approval

Date:	27 September 2016
Project number:	20373
Project title:	*Competitive Advantage of IT Clusters: Assessing technological spill-overs and open innovation*
Risk classification:	Negligible Risk
Chief Investigator:	Professor Prem Chetri
Student Investigator:	Mr Srimannarayana Grandhi
Other Investigator:	Associate Professor Alemayehu Molla
Project Approved:	**From: 13 September 2016** **To: 18 June 2020**

Terms of approval:

Responsibilities of the principal investigator

It is the responsibility of the principal investigator to ensure that all other investigators and staff on a project are aware of the terms of approval and to ensure that the project is conducted as approved by BCHEAN. Approval is only valid while the investigator holds a position at RMIT University.

1. *Amendments*
   Approval must be sought from BCHEAN to amend any aspect of a project including approved documents. To apply for an amendment submit a request for amendment form to the BCHEAN secretary. This form is available on the Human Research Ethics Committee (HREC) website. Amendments must not be implemented without first gaining approval from BCHEAN.
2. *Adverse events*
   You should notify BCHEAN immediately of any serious or unexpected adverse effects on participants or unforeseen events affecting the ethical acceptability of the project.
3. *Participant Information and Consent Form (PICF)*
   The PICF must be distributed to all research participants, where relevant, and the consent form is to be retained and stored by the investigator. The PICF must contain the RMIT University logo and a complaints clause including the above project number.
4. *Annual reports*
   Continued approval of this project is dependent on the submission of an annual report.
5. *Final report*
   A final report must be provided at the conclusion of the project. BCHEAN must be notified if the project is discontinued before the expected date of completion.
6. *Monitoring*
   Projects may be subject to an audit or any other form of monitoring by BCHEAN at any time.
7. *Retention and storage of data*
   The investigator is responsible for the storage and retention of original data pertaining to a project for a minimum period of five years.

Regards,

Associate Professor Penny Weller
Chairperson
RMIT BCHEAN

Appendix C: Survey Questionnaire

Survey Questionnaire

This questionnaire is addressed to the employees in Information Technology industry.

Please answer ALL questions by filling in the blank spaces provided or by checking (✓) the number of the item that BEST describes your situation.

Part I: Background information

1. Name of your organisation:
   ____

2. Location (address) of the organisation:
   ____

3. What are the main products or services of your organisation?
   - ☐ Business Process Outsourcing
   - ☐ IT Marketing
   - ☐ Software development
   - ☐ Maintenance of IT systems
   - ☐ Telecommunications & Networking
   - ☐ IT support
   - ☐ Research and Development
   - ☐ Education, Training and certification authority
   - ☐ Other, please specify_____________

4. Is your organization a Multi-National Organisation?
   - ☐ Yes
   - ☐ No

5. Who are your customers?
   - ☐ Local/Domestic companies
   - ☐ Off-shore companies

6. Number of employees working in your organization:
   - ☐ Less than 20
   - ☐ 20 -50
   - ☐ 51-100

- ☐ 101-200
- ☐ 201-500
- ☐ 501-1000
- ☐ More than 1000

7. Your job title: ____

8. In which of the following areas your job fits in?
   - ☐ Leadership
   - ☐ Marketing/sales
   - ☐ Technology
   - ☐ Consulting
   - ☐ Corporate function
   - ☐ Business process
   - ☐ Research and Development
   - ☐ Education and Training
   - ☐ Other, please specify______________

9. Have you worked in any other IT organization prior to this?
   - ☐ Yes
   - ☐ No

10. Has your organisation received any assistance from the State or Central government?
    - ☐ No
    - ☐ Yes, please specify type of support_____________________(eg. Land, Contract/license, Loan, Grant, Training, Advisory, R&D, Technical assistance)

PART II: Degree of openness

On scale from 1-5, please about your organisation and its willingness to work with other organisations to develop new products and services.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Our organisation maintains up-to-date knowledge about processes, products and services.	1	2	3	4	5
Our organisation's strategy focussed on open innovation, which encourages partnerships with other organisations.	1	2	3	4	5
Our organisation manages its networks with other organisations through regular communications.	1	2	3	4	5
Our organisation has large number of partners in various industries.	1	2	3	4	5
Our organisation has standard business processes to search and acquire external knowledge/technology	1	2	3	4	5
Our organisation continuously searches for potential partners through trade shows and seminars	1	2	3	4	5
Our organisation makes investments in other organisations to gain access to new knowledge/technology	1	2	3	4	5

PART III: Importance of stakeholder engagement

How important are the following stakeholders in open innovation projects? On scale from 1-5, please rate how important are the following stakeholders in open innovation projects?	Not at all important	Somewhat important	Neutral	Important	Very important
Employees	1	2	3	4	5
Customers	1	2	3	4	5
Technology providers	1	2	3	4	5
Education institutions and research organisations	1	2	3	4	5
Competitors	1	2	3	4	5
Start-up companies	1	2	3	4	5

PART IV: Innovation practices

On scale from 1-5, please rate your organisation's open innovation practices.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Our organisation encourages employees to acquire potentially beneficial technologies/ knowhow from external sources.	1	2	3	4	5
Our organisation informs us about the significance of open innovation to organisation's survival.	1	2	3	4	5
Our organisation rewards us for bringing in external technologies and knowledge to improve our products and services.	1	2	3	4	5
Our organisation seeks feedback on proposed new products and services from employees not directly involved in R&D activities.	1	2	3	4	5
Our organisation is supported by its partners in collaborative R&D projects.	1	2	3	4	5
Our organisation facilitates access to external knowledge/technology to help develop new business opportunities to us.	1	2	3	4	5

PART V: Knowledge spill-overs

On scale from 1-5, please rate your organisation's knowledge sharing activities.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Our organisation considers external knowledge/technology to contribute to research and development of new products and services.	1	2	3	4	5
Our organisation considers joint ventures/partnerships to create new knowledge/ technology.	1	2	3	4	5
Our organisation acquires knowledge/technology developed by institutions such as Universities, Professional bodies, R&D laboratories, etc.	1	2	3	4	5
Our organisation involves customers in the development of new products and services.	1	2	3	4	5
Our products and services are developed or redesigned based on customer feedback and their needs.	1	2	3	4	5

PART VI: Inbound innovation

On scale from 1-5, please rate your organisation’s willingness to acquire/utilise external resources to improve business processes and develop new products and services.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Our organisation is willing to buy other organisations IP rights such as trademarks and patents to support/ improve internal business processes.	1	2	3	4	5
Our organisation buys IP rights from others to develop new products and services.	1	2	3	4	5
Our organisation upgrades existing technology to stay ahead of competitors.	1	2	3	4	5

PART VII: Outbound innovation

On scale from 1-5, please rate your organisation’s willingness to share its resources with other organisations.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Our organisation shares its knowledge with other organisations to create new knowledge/ technology.	1	2	3	4	5
Our organisation cooperates with other organisations and supports their projects to gain access to their knowledge/technology.	1	2	3	4	5
Our organisation provides open access to other organisations to use our internal knowledge with little or no cost	1	2	3	4	5
Our organisation shares its knowledge with competitors to absorb resulting knowledge/technology.	1	2	3	4	5
Our organisation sells or licenses its IP rights, patents, etc. to other organisations.	1	2	3	4	5
Our organisation prepares to sell Intellectual Property (IP) rights such as trademarks and patents for profit.	1	2	3	4	5
Our organisation is willing to enter into partnerships to introduce and promote new products and services.	1	2	3	4	5

PART VIII: Absorptive capacity

On scale from 1-5, please rate your organisation's capability to absorb new knowledge.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Our organisation has the capability to utilise new knowledge to organisation's benefit.	1	2	3	4	5
Our organisation has the capability to develop new products and services by using external knowledge.	1	2	3	4	5
Our organisation has the capability to develop alternative solutions by using external knowledge.	1	2	3	4	5
Our organisation has the capability to integrate new knowledge with existing knowledge.	1	2	3	4	5
Our organisation has the capability to redesign existing business processes through absorbing new knowledge.	1	2	3	4	5

PART IX: Innovation performance

On scale from 1-5, please rate your organisation's innovation performance in the last three years. In the last three years our organisation has performed worse/better than competitors in relation to:	Much lower than competitors	Lower than competitors	No change	Higher than competitors	Much higher than competitors
Process innovation	1	2	3	4	5
Product innovation	1	2	3	4	5
Service innovation	1	2	3	4	5
Intellectual property rights	1	2	3	4	5

Appendix D: Multivariate Outlier Test Results

Case	D^2	D^2/df	Mean	SD	Case	D^2	D^2/df	Mean	SD	Case	D^2	D^2/df	Mean	SD	Case	D^2	D^2/df	Mean	SD
1	23.47	0.98	4.00	0.60	55	5.69	1.00	3.93	0.25	109	23.51	0.98	4.18	0.61	163	20.14	1.00	4.70	0.46
2	22.49	0.99	3.91	0.67	56	23.10	0.99	3.41	0.72	110	42.03	0.38	2.95	0.90	164	34.19	0.73	3.84	0.80
3	43.50	0.32	4.39	0.71	57	30.80	0.85	3.41	0.75	111	34.54	0.71	3.86	0.59	165	52.63	0.09	3.68	1.18
4	35.75	0.66	4.11	0.68	58	6.35	1.00	4.95	0.21	112	32.97	0.78	4.25	0.83	166	39.82	0.48	3.98	0.81
5	35.24	0.68	4.48	0.58	59	37.66	0.58	3.84	0.95	113	32.37	0.80	3.05	0.77	167	35.88	0.66	4.55	0.58
6	55.77	0.05	4.34	0.90	60	32.42	0.80	4.14	0.79	114	31.96	0.81	4.11	0.83	168	12.75	1.00	3.16	0.42
7	31.58	0.83	3.25	0.57	61	77.84	0.00	3.23	1.22	115	30.92	0.85	4.32	0.55	169	42.86	0.35	3.18	0.98
8	50.32	0.13	3.30	0.99	62	44.52	0.29	3.70	0.97	116	36.63	0.62	4.39	0.75	170	31.53	0.83	3.91	0.82
9	34.49	0.72	3.61	0.53	63	60.17	0.02	3.84	0.82	117	16.78	1.00	4.57	0.62	171	66.78	0.00	3.82	0.91
10	46.06	0.24	3.75	0.80	64	41.75	0.39	4.20	0.62	118	48.37	0.17	4.11	0.93	172	34.53	0.71	4.64	0.64
11	53.64	0.07	4.05	0.93	65	12.22	1.00	4.89	0.32	119	27.05	0.94	4.43	0.54	173	40.42	0.45	4.84	0.67
12	62.40	0.01	3.98	1.16	66	21.92	0.99	3.77	0.47	120	20.92	0.99	4.61	0.49	174	47.25	0.20	4.30	0.66
13	24.42	0.98	4.25	0.48	67	12.69	1.00	4.16	0.37	121	50.07	0.13	3.77	0.73	175	58.87	0.03	3.89	1.15
14	14.96	1.00	4.09	0.47	68	55.56	0.05	3.93	0.72	122	35.20	0.69	4.25	0.57	176	60.29	0.02	3.57	0.86
15	16.80	1.00	4.07	0.33	69	32.83	0.78	2.98	0.99	123	36.81	0.61	3.30	0.94	177	21.88	0.99	3.93	0.58
16	33.49	0.76	4.16	0.64	70	42.29	0.37	1.27	0.49	124	53.76	0.07	3.48	0.81	178	34.64	0.71	3.98	0.62
17	37.47	0.58	2.75	0.64	71	41.95	0.39	4.07	0.84	125	41.86	0.39	3.61	0.68	179	53.10	0.08	3.59	0.83
18	31.65	0.82	4.43	0.50	72	19.22	1.00	3.95	0.47	126	30.79	0.85	4.50	0.50	180	40.60	0.44	4.50	0.54
19	38.24	0.55	4.34	0.56	73	30.53	0.86	3.43	0.72	127	37.11	0.60	4.39	0.65	181	22.62	0.99	4.75	0.43

20	41.08	0.42	3.36	0.61	74	35.48	0.67	3.20	0.89	128	58.56	0.03	3.18	1.09	182	26.92	0.94	4.57	0.50
21	42.32	0.37	4.18	0.68	75	38.95	0.52	3.52	0.92	129	24.20	0.98	4.36	0.53	183	46.29	0.23	3.98	0.84
22	38.39	0.54	4.16	0.67	76	74.69	0.00	4.23	0.79	130	36.32	0.64	4.45	0.66	184	31.83	0.82	3.73	0.75
23	34.40	0.72	3.73	0.54	77	38.09	0.56	3.45	0.54	131	20.65	1.00	4.66	0.47	185	21.93	0.99	4.23	0.60
24	54.40	0.06	3.70	0.73	78	62.76	0.01	2.82	1.07	132	32.40	0.80	4.59	0.61	186	33.15	0.77	3.93	0.81
25	65.14	0.01	1.93	0.78	79	30.58	0.86	4.27	0.75	133	65.39	0.01	3.32	1.29	187	28.84	0.90	4.68	0.47
26	65.44	0.01	4.00	0.74	80	56.14	0.05	2.09	0.76	134	17.34	1.00	4.70	0.46	188	53.86	0.07	3.98	0.87
27	61.28	0.02	2.07	0.75	81	76.62	0.00	4.11	1.07	135	19.42	1.00	3.91	0.60	189	65.82	0.01	3.64	0.86
28	22.22	0.99	4.66	0.74	82	28.06	0.92	4.34	0.67	136	46.73	0.22	4.00	0.98	190	58.89	0.03	4.32	0.70
29	45.07	0.27	3.89	0.91	83	27.88	0.93	3.43	0.75	137	38.58	0.53	2.70	0.89	191	89.30	0.00	2.89	1.32
30	62.84	0.01	2.48	0.92	84	16.18	1.00	4.45	0.50	138	24.66	0.97	4.64	0.48	192	50.60	0.12	4.45	0.69
31	66.60	0.01	3.82	1.05	85	45.01	0.27	3.32	1.10	139	28.39	0.92	4.07	0.75	193	67.12	0.00	3.61	1.11
32	41.65	0.40	4.32	0.67	86	30.91	0.85	4.20	0.69	140	37.78	0.57	2.91	0.90	194	39.09	0.51	4.41	0.72
33	27.54	0.93	4.64	0.61	87	24.90	0.97	3.86	0.55	141	40.68	0.44	4.25	0.57	195	25.44	0.96	3.32	0.79
34	27.48	0.93	4.34	0.47	88	45.81	0.24	3.50	0.87	142	16.82	1.00	4.20	0.62	196	57.15	0.04	4.11	0.80
35	51.63	0.10	1.98	0.72	89	29.04	0.90	4.41	0.49	143	32.36	0.80	4.00	0.77	197	29.95	0.88	3.43	0.78
36	41.21	0.42	4.50	0.75	90	46.56	0.22	4.20	0.73	144	26.12	0.96	3.91	0.47	198	84.03	0.00	3.50	0.97
37	78.25	0.00	3.80	1.01	91	28.54	0.91	2.80	0.84	145	51.89	0.10	3.66	0.67	199	27.02	0.94	4.23	0.63
38	95.59	0.00	3.34	1.22	92	36.30	0.64	3.52	0.84	146	32.12	0.81	3.27	0.49	200	34.11	0.73	4.34	0.74
39	27.66	0.93	3.70	0.66	93	48.03	0.18	3.20	1.14	147	30.39	0.86	4.32	0.55	201	57.50	0.04	4.00	1.07
40	23.03	0.99	4.66	0.47	94	32.90	0.78	4.52	0.66	148	43.08	0.34	3.34	0.82	202	36.21	0.64	4.59	0.81
41	21.49	0.99	3.95	0.52	95	56.36	0.04	3.73	1.12	149	24.80	0.97	4.57	0.50	203	27.27	0.94	4.64	0.48
42	45.06	0.27	3.93	0.99	96	61.66	0.02	3.18	1.09	150	36.07	0.65	2.80	0.99	204	41.76	0.39	4.52	0.69
43	21.88	0.99	4.73	0.58	97	29.98	0.88	4.43	0.54	151	19.52	1.00	4.43	0.50	205	43.78	0.31	4.20	0.97

44	9.39	1.00	4.09	0.47	98	76.96	0.00	3.23	1.20	152	28.55	0.91	3.89	0.68	206	73.58	0.00	3.75	1.13
45	24.96	0.97	3.32	0.70	99	52.04	0.10	3.70	0.76	153	37.88	0.57	2.93	0.96	207	41.18	0.42	3.57	1.01
46	5.60	1.00	4.98	0.15	100	34.76	0.70	4.34	0.60	154	36.81	0.61	4.11	0.83	208	41.03	0.43	3.45	0.84
47	22.02	0.99	4.66	0.56	101	22.07	0.99	3.41	0.72	155	40.55	0.45	2.91	0.95	209	44.36	0.29	3.64	0.77
48	35.13	0.69	3.93	0.78	102	42.52	0.36	3.95	0.67	156	30.36	0.86	4.07	0.75	210	35.95	0.65	3.75	0.74
49	20.89	0.99	4.70	0.50	103	62.96	0.01	3.16	1.20	157	54.08	0.07	4.16	0.67	211	32.35	0.80	3.25	0.91
50	27.67	0.93	3.25	0.91	104	40.15	0.46	4.43	0.58	158	36.55	0.63	4.25	0.53	212	34.54	0.71	3.20	0.92
51	12.57	1.00	3.91	0.42	105	40.05	0.47	4.27	0.62	159	28.85	0.90	3.36	0.53	213	41.05	0.42	3.09	0.92
52	6.96	1.00	3.05	0.21	106	47.80	0.19	3.91	1.06	160	37.91	0.56	4.39	0.57	214	36.81	0.61	4.61	0.75
53	22.41	0.99	3.45	0.75	107	84.59	0.00	3.36	1.35	161	48.87	0.16	3.93	0.78	215	85.74	0.00	4.23	0.90
54	37.84	0.57	3.66	0.74	108	23.17	0.98	4.86	0.40	162	26.64	0.95	3.48	0.69	216	34.88	0.70	4.34	0.80

Case	D^2	D^2/df	Mean	SD	Case	D^2	D^2/df	Mean	SD	Case	D^2	D^2/df	Mean	SD	Case	D^2	D^2/df	Mean	SD
217	74.72	0.00	3.14	0.89	250	75.93	0.00	3.98	0.84	283	78.64	0.00	3.45	0.94	316	12.67	1.00	4.11	0.38
218	71.44	0.00	3.93	0.94	251	74.74	0.00	2.86	1.18	284	38.44	0.54	3.95	0.71	317	4.37	1.00	3.93	0.25
219	50.11	0.13	3.30	0.87	252	77.55	0.00	3.82	1.27	285	42.25	0.37	3.86	0.73	318	3.15	1.00	5.00	0.00
220	35.20	0.69	4.14	0.69	253	110.15	0.00	2.84	1.24	286	51.48	0.11	1.77	0.67	319	11.75	1.00	4.89	0.38
221	64.97	0.01	3.52	0.89	254	57.74	0.03	4.18	0.75	287	80.91	0.00	2.25	0.83	320	3.15	1.00	5.00	0.00
222	57.34	0.04	4.25	0.77	255	28.38	0.92	4.52	0.58	288	37.56	0.58	2.41	0.65	321	3.15	1.00	4.98	0.15
223	37.62	0.58	4.25	0.64	256	84.50	0.00	3.70	0.99	289	67.18	0.00	2.09	0.76	322	3.15	1.00	5.00	0.00
224	35.61	0.67	4.27	0.69	257	93.09	0.00	3.61	1.15	290	47.47	0.19	2.84	0.80	323	3.15	1.00	5.00	0.00
225	66.24	0.01	3.25	0.86	258	35.24	0.68	4.39	0.78	291	41.04	0.42	3.91	0.79	324	32.61	0.79	4.68	0.47
226	66.21	0.01	3.55	1.03	259	35.45	0.68	4.18	0.86	292	37.28	0.59	2.57	0.50	325	3.15	1.00	5.00	0.00
227	82.47	0.00	3.64	1.07	260	76.69	0.00	3.64	1.07	293	35.11	0.69	2.55	0.50	326	3.15	1.00	5.00	0.00
228	68.62	0.00	3.45	0.81	261	101.02	0.00	2.05	1.26	294	46.40	0.23	2.27	0.65	327	3.15	1.00	5.00	0.00

229	49.41	0.15	4.34	0.71	262	75.87	0.00	3.80	0.89	295	72.00	0.00	2.25	0.77	328	3.15	1.00	5.00	0.00
230	24.36	0.98	4.48	0.66	263	15.58	1.00	3.93	0.45	296	72.31	0.00	2.20	0.76	329	3.65	1.00	3.00	0.00
231	23.67	0.98	4.02	0.54	264	88.67	0.00	3.84	1.00	297	71.86	0.00	2.05	0.80	330	3.15	1.00	5.00	0.00
232	35.93	0.65	3.80	0.94	265	35.40	0.68	2.64	0.48	298	54.48	0.06	2.11	0.78	331	3.15	1.00	5.00	0.00
233	47.14	0.20	4.00	0.74	266	64.20	0.01	3.39	0.88	299	73.99	0.00	2.00	0.80	332	3.15	1.00	5.00	0.00
234	23.25	0.98	3.75	0.57	267	30.59	0.86	2.80	0.55	300	61.82	0.01	2.25	0.71	333	3.15	1.00	5.00	0.00
235	46.96	0.21	3.18	0.91	268	51.19	0.11	3.70	0.73	301	63.00	0.01	3.86	0.97	334	3.15	1.00	5.00	0.00
236	88.18	0.00	3.93	0.96	269	8.41	1.00	3.98	0.34	302	87.87	0.00	2.00	0.80	335	10.31	1.00	4.86	0.34
237	65.52	0.01	2.00	0.77	270	49.43	0.15	1.95	0.60	303	49.38	0.15	2.66	0.88	336	17.18	1.00	4.84	0.37
238	73.22	0.00	3.86	0.97	271	53.49	0.08	2.36	0.68	304	55.13	0.06	3.73	0.96	337	10.32	1.00	4.93	0.25
239	36.51	0.63	2.89	1.00	272	60.85	0.02	2.02	0.75	305	79.44	0.00	4.05	1.17	338	12.01	1.00	4.93	0.25
240	67.71	0.00	4.02	0.87	273	49.57	0.14	4.05	0.74	306	46.93	0.21	1.39	0.57	339	16.00	1.00	4.89	0.32
241	29.38	0.89	4.07	0.75	274	60.08	0.02	3.61	1.11	307	6.44	1.00	3.95	0.30	340	14.50	1.00	4.84	0.37
242	53.79	0.07	4.27	0.86	275	59.19	0.03	2.00	0.74	308	14.17	1.00	4.86	0.34	341	12.95	1.00	4.93	0.25
243	38.36	0.54	3.95	0.67	276	21.19	0.99	4.80	0.50	309	20.20	1.00	4.16	0.37	342	13.68	1.00	4.86	0.34
244	68.44	0.00	4.00	0.88	277	71.47	0.00	1.84	0.85	310	19.00	1.00	4.73	0.45	343	9.67	1.00	4.89	0.32
245	68.21	0.00	3.05	1.22	278	59.19	0.03	2.18	0.75	311	4.45	1.00	4.07	0.25	344	8.26	1.00	3.95	0.30
246	45.23	0.26	4.05	0.77	279	60.33	0.02	4.23	0.90	312	1.33	1.00	4.00	0.00	345	9.74	1.00	2.93	0.25
247	57.92	0.03	3.98	0.75	280	45.01	0.27	3.16	0.74	313	1.33	1.00	4.05	0.21	346	10.07	1.00	4.91	0.36
248	65.46	0.01	3.39	0.86	281	45.16	0.27	4.41	1.01	314	1.33	1.00	4.00	0.00					
249	42.01	0.38	3.30	0.62	282	86.22	0.00	4.43	1.01	315	1.33	1.00	4.00	0.00					